Range Filters

(SuRF, Memento Filter, Diva)

Niv Dayan - CSC2525: Research Topics in Database Management

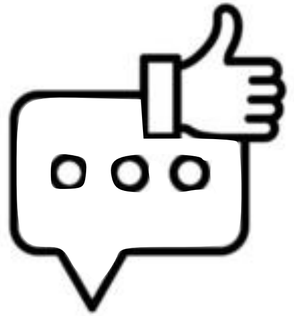
Last lecture

This was fun…

Logistics

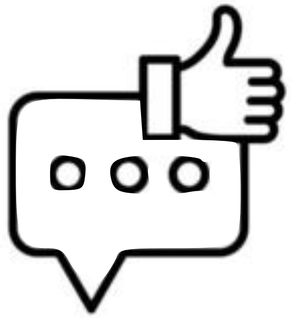
Projects due
on April 15

Exam
April 30



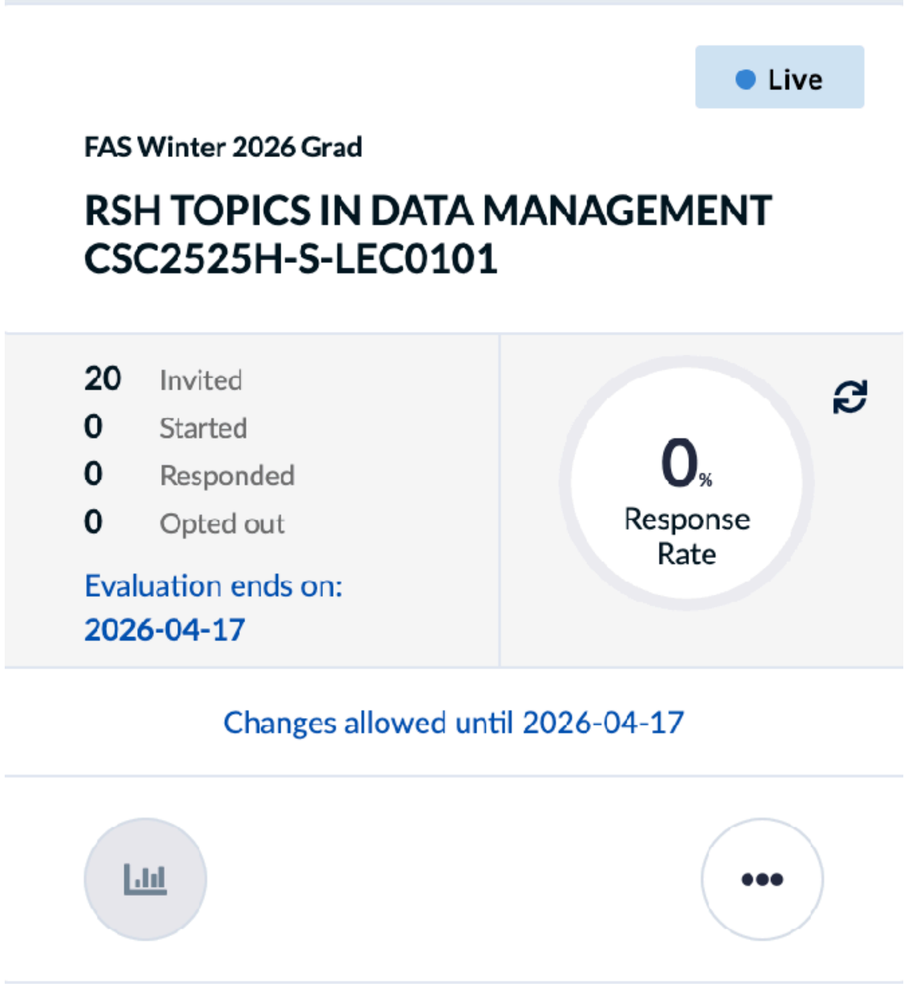
Course
Evaluation

Course Evaluation

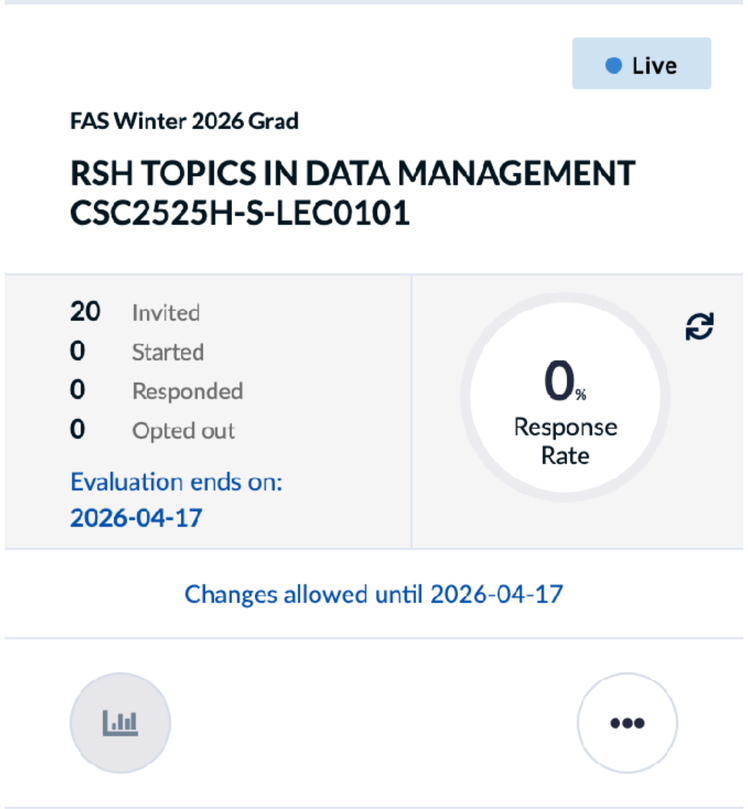


Helps us improve

Course Evaluation



Course Evaluation



No excuses :)

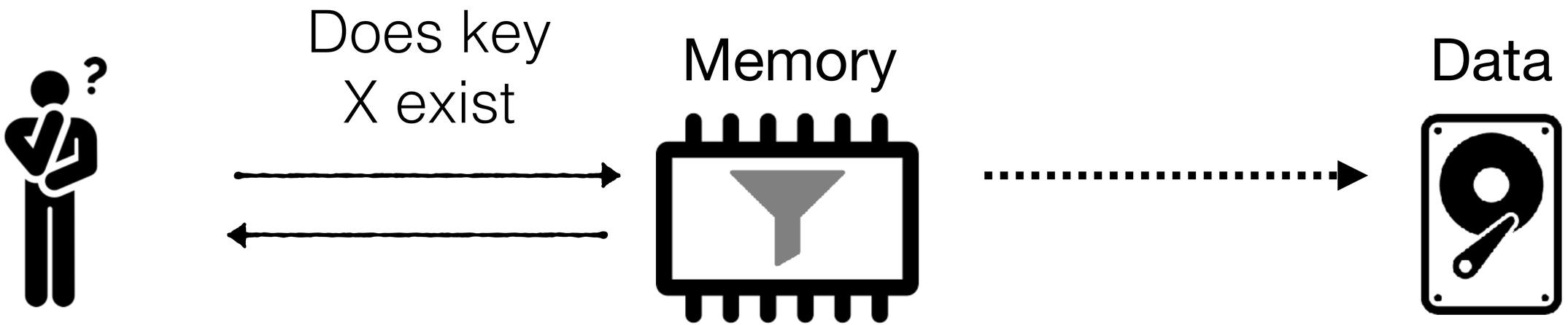
What is a Filter?

Does X exist? 

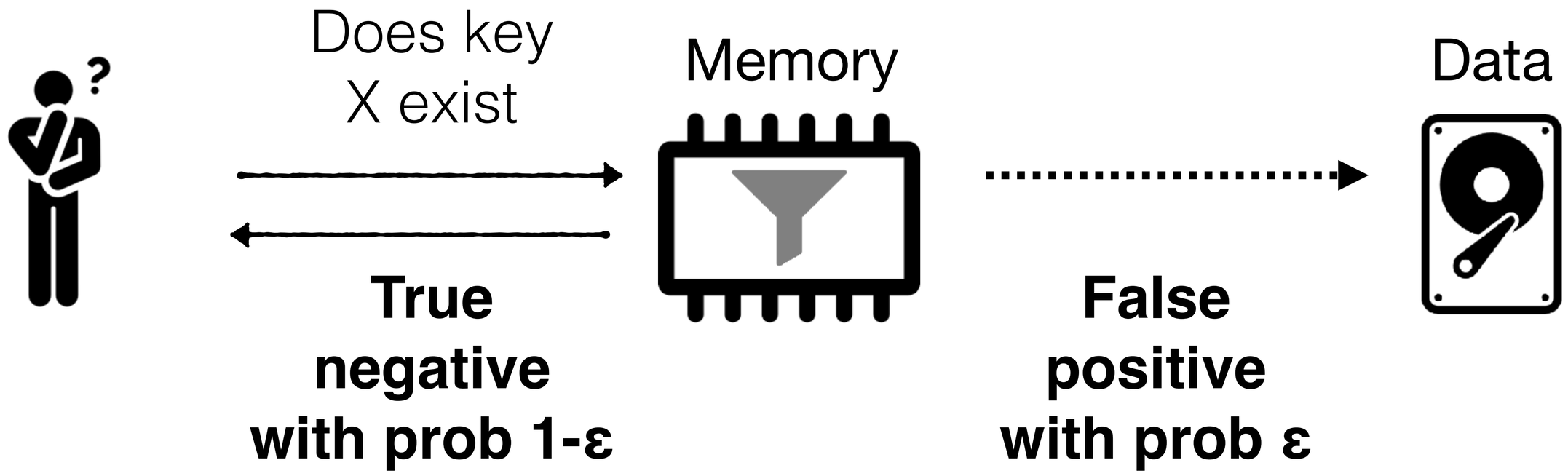
Set

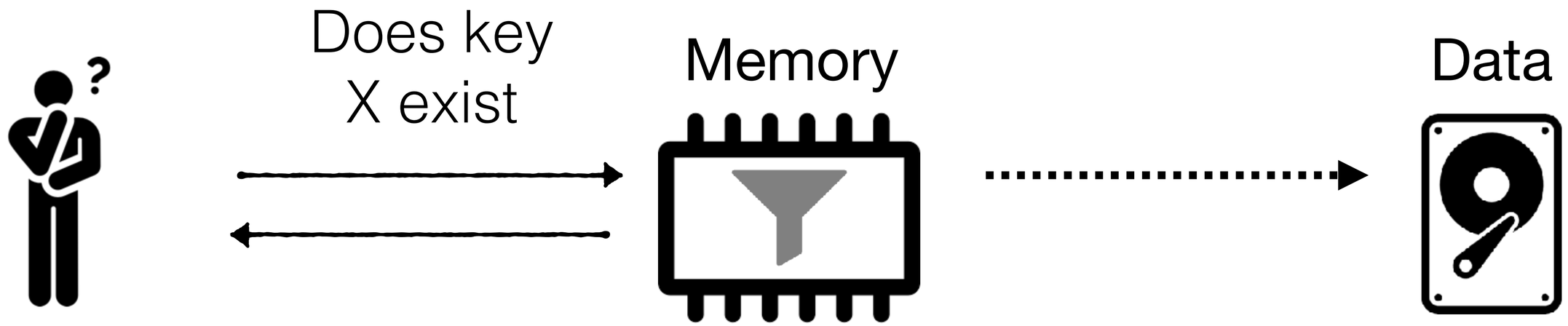
X Y Z

If key X does not exist



If key X does not exist





Saves storage accesses & network hops

only support point queries (to one key)

Does X exist? 

Set

X Y Z

only support point queries (to one key)

How about a range?

Does X exist? 

Set

X Y Z

How about a range?

Does anything in [A, B] exist?

Set

X Y Z

How about a range?

Does anything in [3, 5] exist?

Set

1 4 9

How about a range?

Does anything in
[3, 5] exist?

True positive

Set

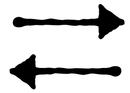
1 4 9

Does anything in
[5, 8] exist?

Set

1 4 9

Does anything in
[5, 8] exist?



Set

1 4 9

**True negative
with prob 1-ε**

Does anything in
[5, 8] exist?

Set

1 4 9

True negative with prob 1-ε

False positive with prob ε

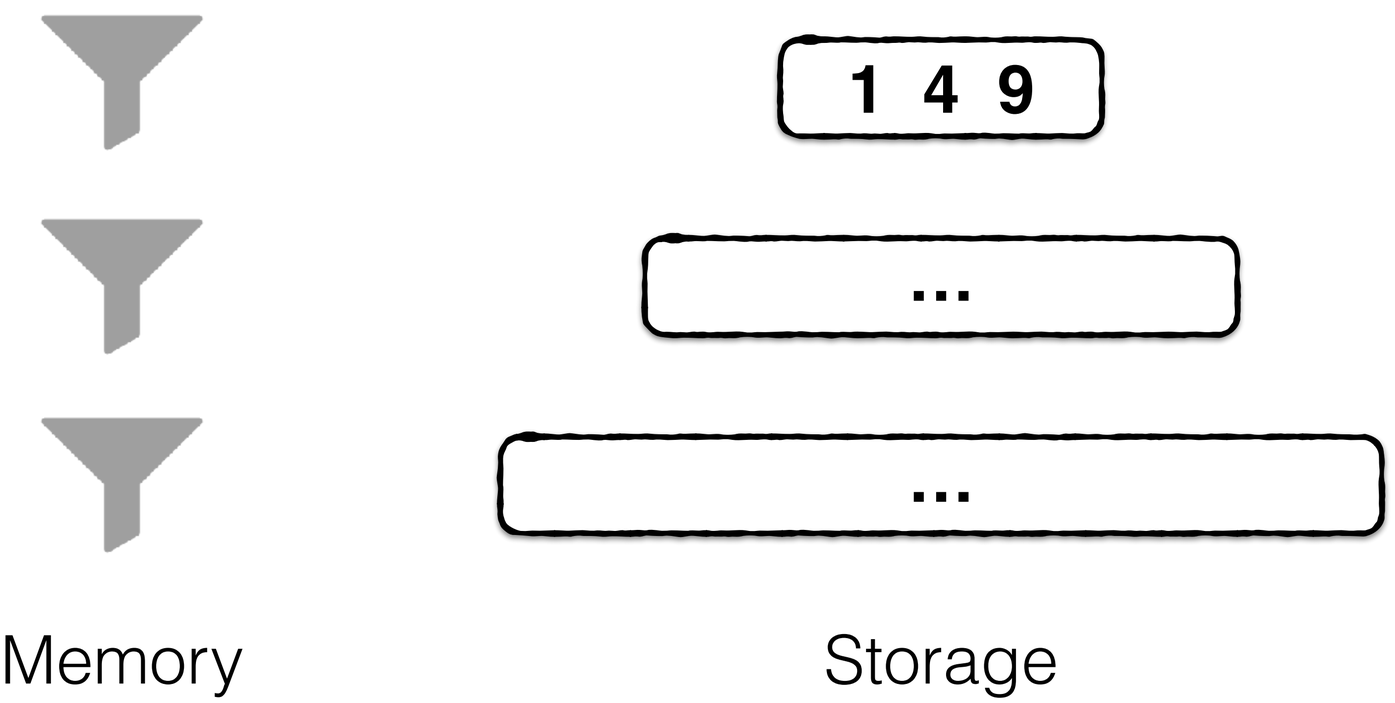
Applications?

Does anything in [5, 8] exist?

True negative with prob 1-ε

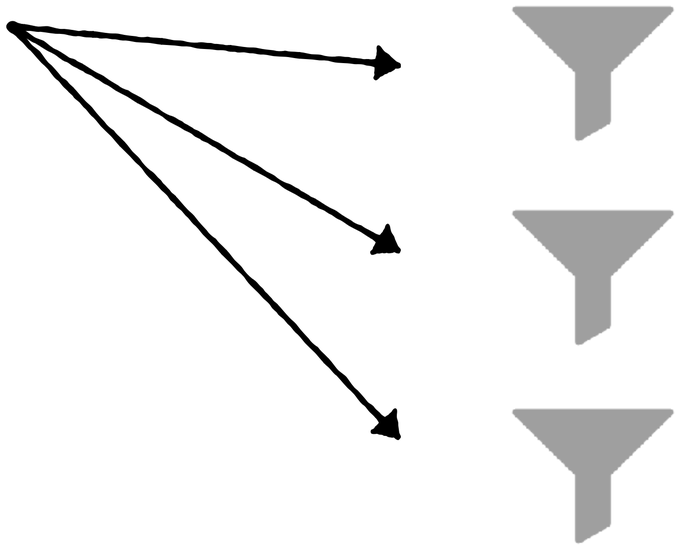
False positive with prob ε

Does anything in
[5, 8] exist?

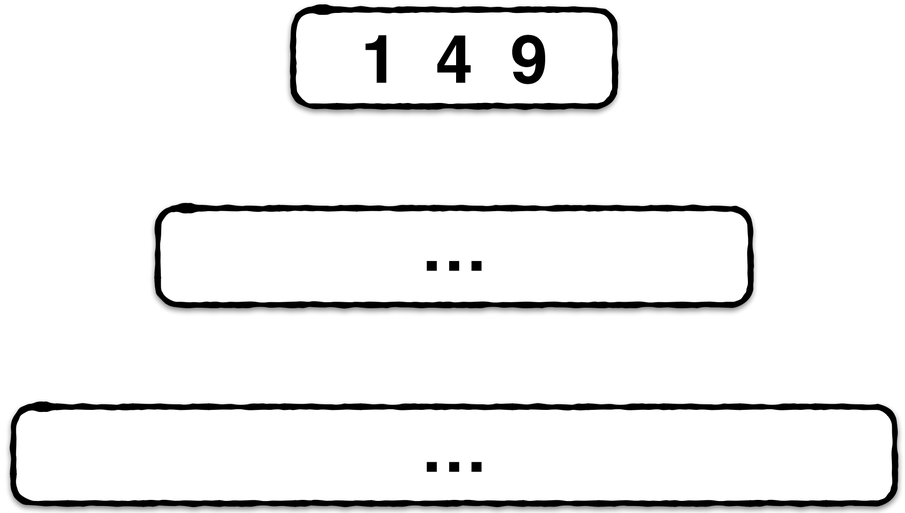


Does anything in [A, B] exist?

Filters

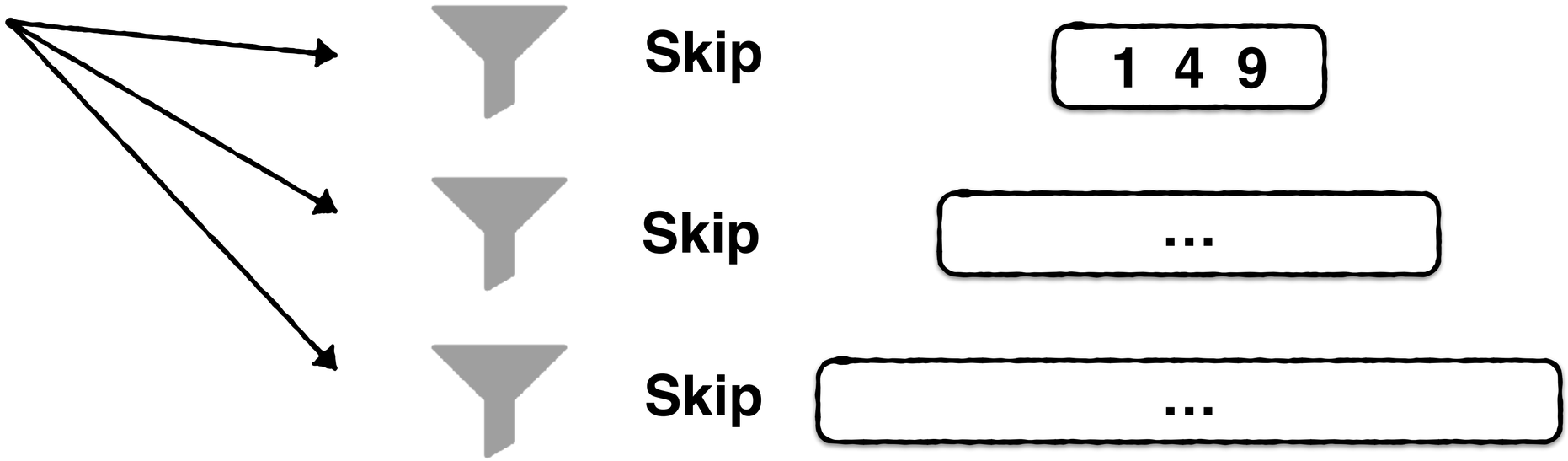


LSM-tree



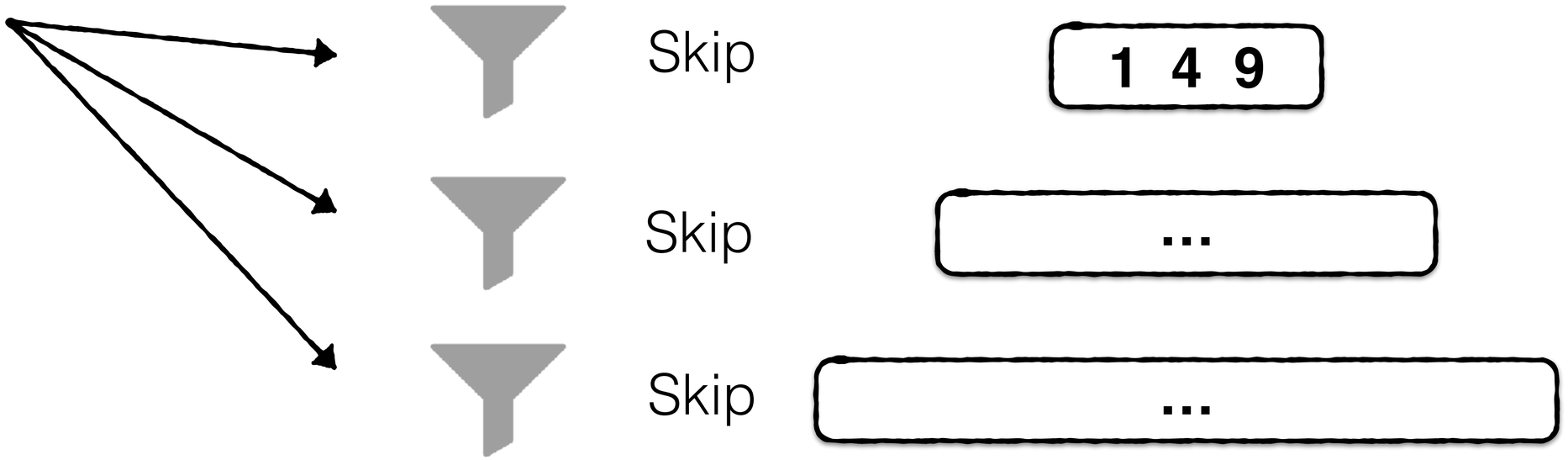
Ideally skip runs that don't contain relevant key range

Does anything in
[A, B] exist?



How to implement a range filter?

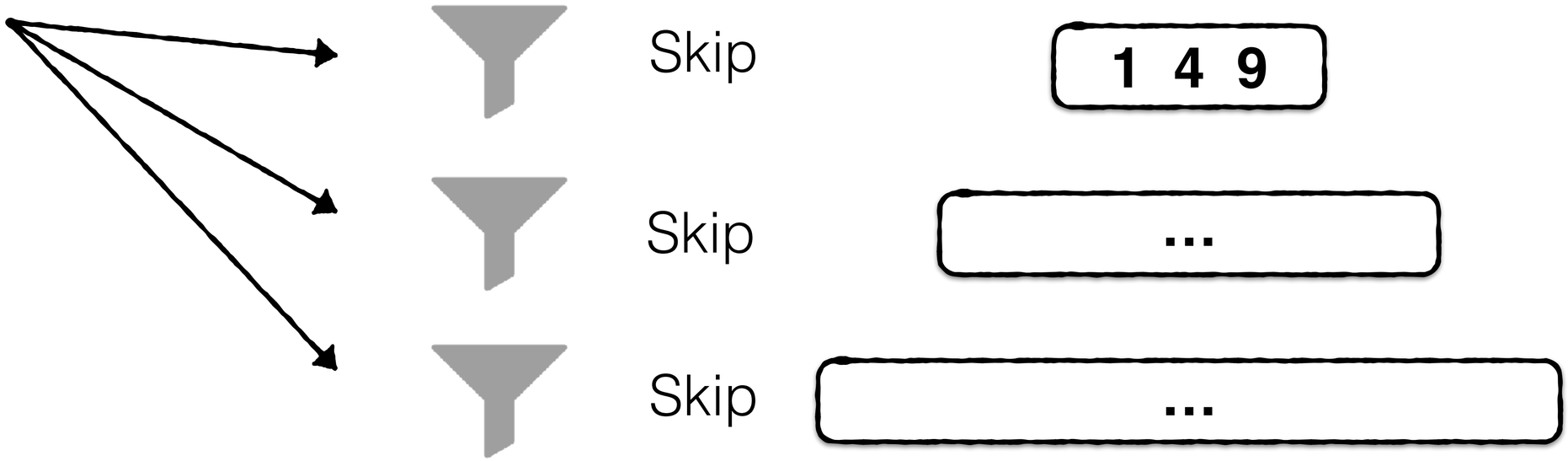
Does anything in
[A, B] exist?



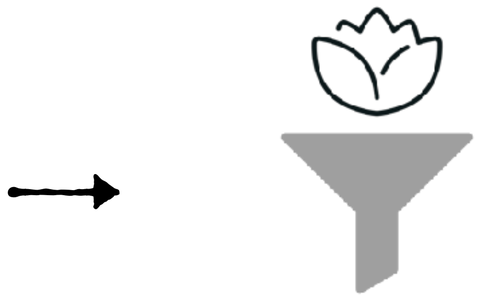
How to implement a range filter?

Can we use a point filter (Bloom, Quotient) to answer range queries?

Does anything in
[A, B] exist?



Does anything in
[5, 8] exist?



Set

1 4 9

Query every key in range

Does anything in **[5, 8]** exist?

Check 5

Check 6

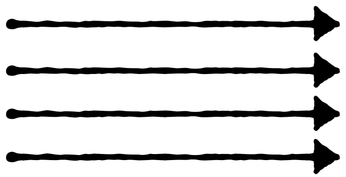
Check 7

Check 8

Query every key in range

Does anything in **[A, B]** exist?

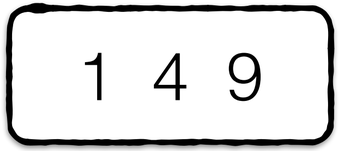
R queries



R = B - A + 1

Bloom

Set

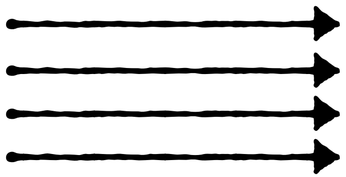


If all queries return negative, we know key does not exist

Query every key in range

Does anything in **[A, B]** exist?

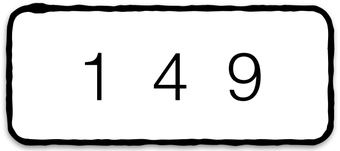
R queries



R = B - A

Bloom

Set

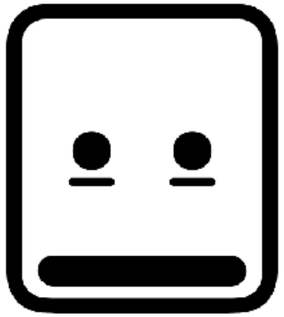


If all queries return negative, we know key does not exist

If at least one returns a positive, the overall outcome is a positive

Query every key in range

Problems?

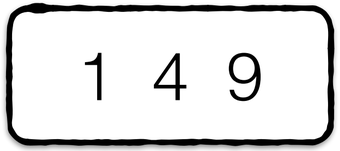


Does anything in [A, B] exist?

R queries

Bloom

Set

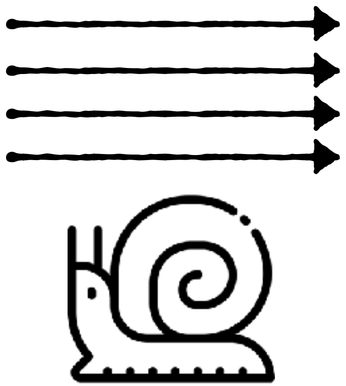


If all queries return negative, we know key does not exist

If at least one returns a positive, the overall outcome is a positive

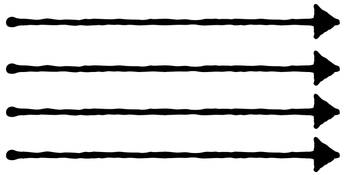
Problem 1: Query Cost

Does anything in [A, B] exist?



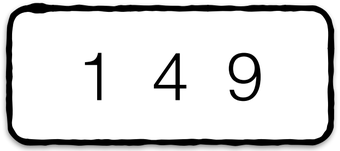
Problem 2: Does not work for infinite universe (e.g., strings)

Does anything in [A, B] exist?



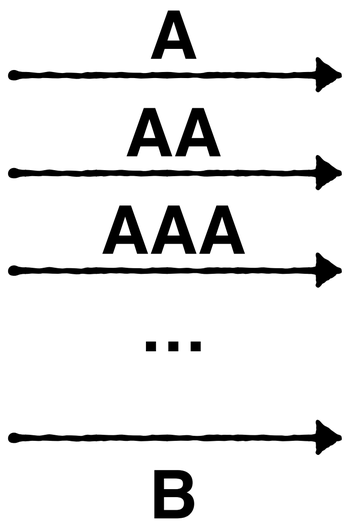
Bloom

Set



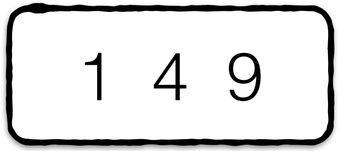
Problem 2: Does not work for infinite universe (e.g., strings)

Does anything in [A, B] exist?



Bloom

Set



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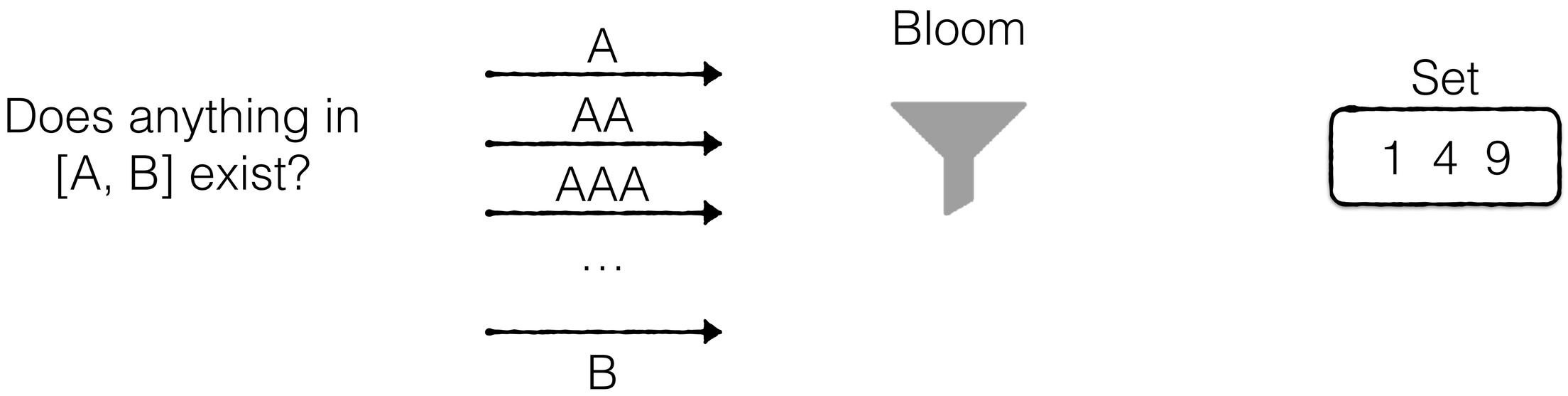


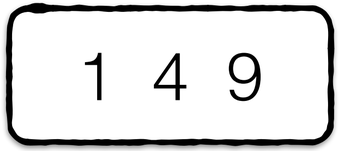
There are infinitely many possible keys in a range :)

Problem 3: Higher False Positive Rate

Does anything in [A, B] exist?

Bloom

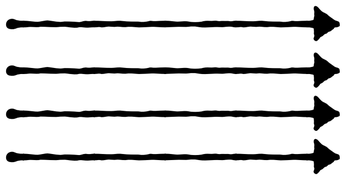
Set



Problem 3: Higher False Positive Rate

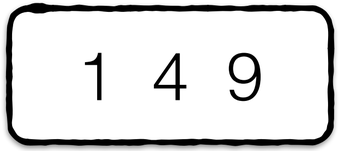
Does anything in [A, B] exist?

R queries



FPR ε

Set



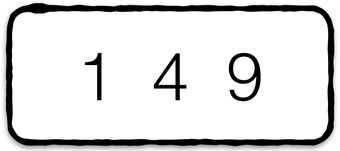
Problem 3: Higher False Positive Rate

Does anything in [A, B] exist?

R queries

FPR ε

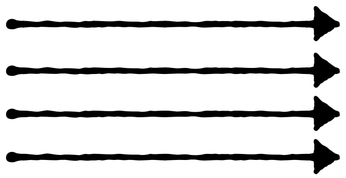
Set



P[false positive]?

Problem 3: Higher False Positive Rate

Does anything in [A, B] exist?



P[false positive] = P[at least one query returns positive]

Problem 3: Higher False Positive Rate

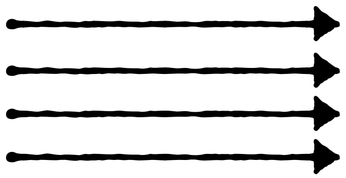
Does anything in [A, B] exist?

P[false positive] = P[at least one query returns positive]

= 1 - P[all queries return negative]

Problem 3: Higher False Positive Rate

Does anything in [A, B] exist?



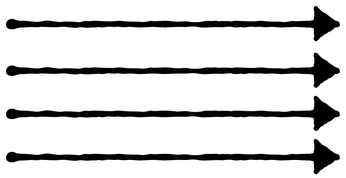
P[false positive] = P[at least one query returns positive]

= 1 - P[all queries return negative]

= 1 - P[one query return negative]^R

Problem 3: Higher False Positive Rate

Does anything in [A, B] exist?



P[false positive] = P[at least one query returns positive]

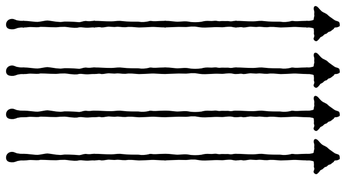
= 1 - P[all queries return negative]

= 1 - P[one query return negative]^R

= 1 - (1-ε)^R

Problem 3: Higher False Positive Rate

Does anything in [A, B] exist?



$$
\begin{aligned}
\text{P[false positive]} &= \text{P[at least one query returns positive]} \\
&= 1 - \text{P[all queries return negative]} \\
&= 1 - \text{P[one query return negative]}^{R} \\
&= 1 - (1-\varepsilon)^{R} \\
&\approx \mathbf{1 - e^{\varepsilon \cdot R}}
\end{aligned}
$$

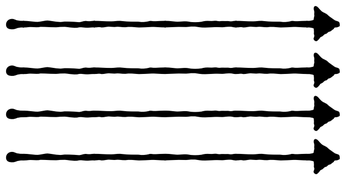
Problem 3: Higher False Positive Rate

Does anything in [A, B] exist?

$$
\begin{aligned}
\text{P[false positive]} &= \text{P[at least one query returns positive]} \\
&= 1 - \text{P[all queries return negative]} \\
&= 1 - \text{P[one query return negative]}^{R} \\
&= 1 - (1-\varepsilon)^{R} \\
&\approx 1 - e^{\varepsilon \cdot R} \\
&< \boldsymbol{\varepsilon \cdot R} \qquad \textbf{By union bound}
\end{aligned}
$$

Problem 3: Higher False Positive Rate

Does anything in [A, B] exist?



P[false positive] < ε · R

Problem 3: Higher False Positive Rate

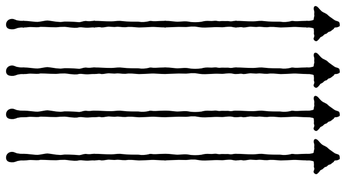
Does anything in [A, B] exist?

$$P[\text{false positive}] < \varepsilon \cdot R$$

Useless for large R

Problem 3: Higher False Positive Rate

Does anything in [A, B] exist?

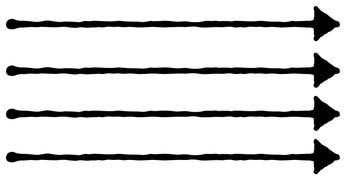


$$P[\text{false positive}] < \boldsymbol{\varepsilon} \cdot R$$

Recall that: $\boldsymbol{\varepsilon = 2^{-F}}$ **where F = bits / entry**

Problem 3: Higher False Positive Rate

Does anything in [A, B] exist?

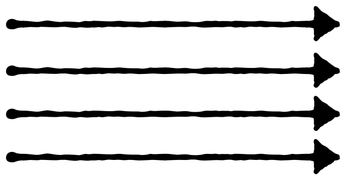


$$P[\text{false positive}] < \mathbf{2^{-F}} \cdot R$$

How many extra bits per entry do we need to make up for R?

Problem 3: Higher False Positive Rate

Does anything in [A, B] exist?



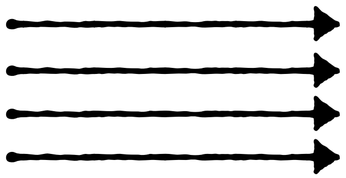
$$P[\text{false positive}] < \mathbf{2^{-F}} \cdot R$$

How many extra bits per entry do we need to make up for R?

$\log_2(R)$

Problem 3: Higher False Positive Rate

Does anything in [A, B] exist?



$$P[\text{false positive}] < 2^{-F - \log_2(R)} \cdot R$$

How many extra bits per entry do we need to make up for R?

Problem 3: Higher False Positive Rate

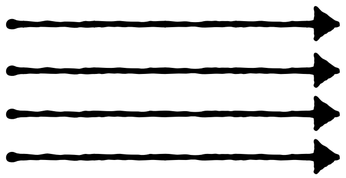
Does anything in [A, B] exist?

$$P[\text{false positive}] < 2^{-F} \cdot \cancel{\log_2(R)} \cdot \cancel{R}$$

How many extra bits per entry do we need to make up for R?

Problem 3: Higher False Positive Rate

Does anything in [A, B] exist?



$$P[\text{false positive}] < 2^{-F - \log_2(R)} \cdot R$$

FPR is higher by factor of R, or we need $\log_2(R)$ extra bits / entry to keep it stable

Problem 3: Higher False Positive Rate

Does anything in [A, B] exist?

$$P[\text{false positive}] < 2^{-F - \log_2(R)} \cdot \cancel{R}$$

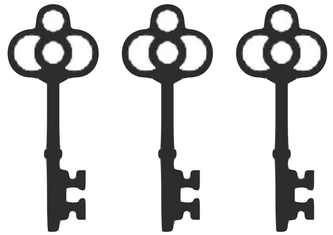
FPR is higher by factor of R, or we need $\log_2(R)$ extra bits / entry to keep it stable

But this also requires us to know max range query length in advance

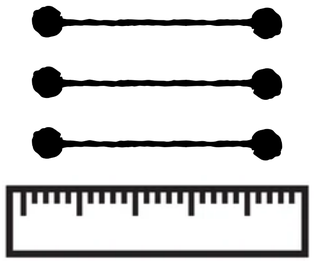
Problems

query cost
O(R)

FPR
O(ε · R)



Fixed-length
keys



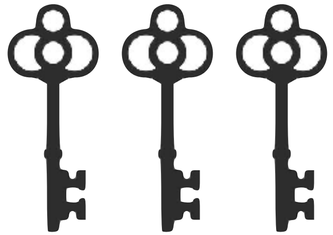
Bounded
queries

Problems

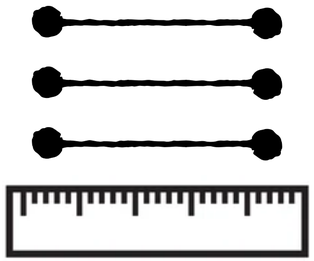
How much can we improve these?

query cost
O(R)

FPR
O(ε · R)



Fixed-length
keys



Bounded
queries

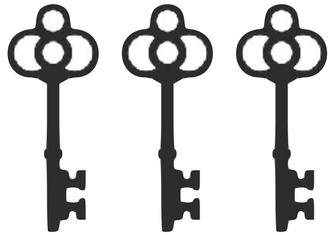
How much can we improve these?

query cost
O(1)

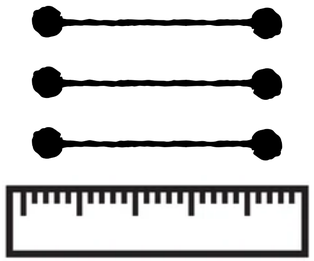
↑

?

FPR
$O(\varepsilon \cdot R)$



Fixed-length
keys



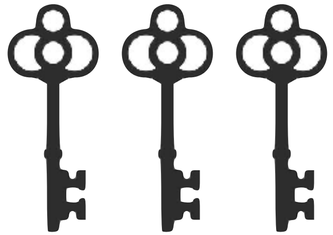
Bounded
queries

How much can we improve these?

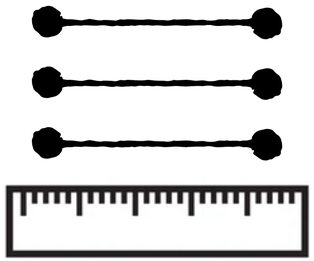
query cost
O(1)

FPR
$O(\varepsilon \cdot \cancel{R})$

?



Fixed-length
keys

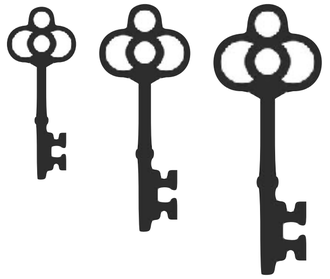


Bounded
queries

How much can we improve these?

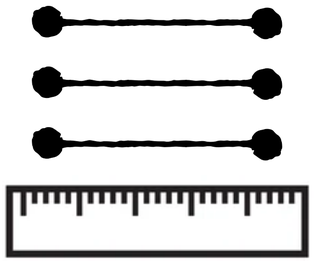
query cost
O(1)

FPR
O(ε)



Var-length keys

?

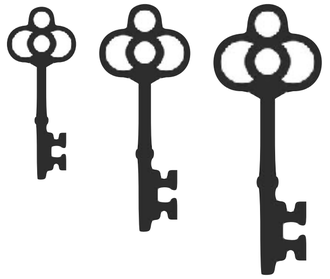


Bounded queries

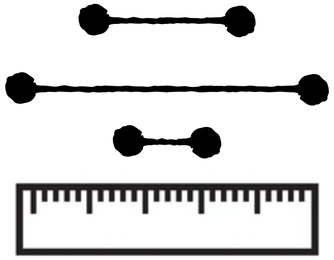
How much can we improve these?

query cost
O(1)

FPR
O(ε)



Var-length
keys



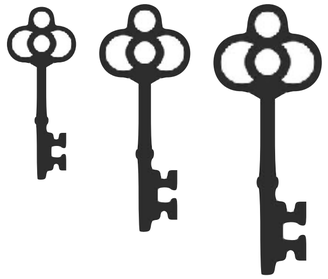
Var-length queries

↑

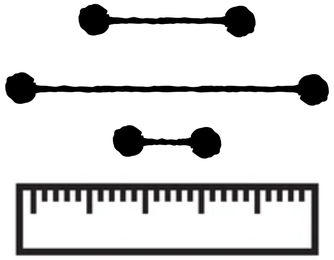
?

query cost
O(1)

FPR
O(ε)



Var-length
keys



Var-length
queries

+ Dynamic operations

(Inserts, deletes, expansions, contractions)

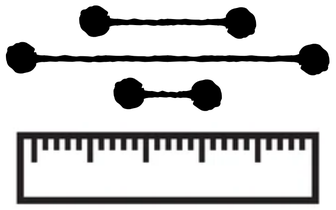
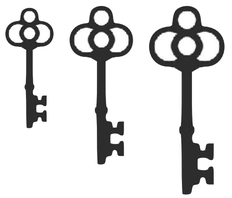
Hot research topic in past decade

SuRF SIGMOD18	**Rosetta** SIGMOD2020	**SNARF** SIGMOD22	**Proteus** SIGMOD22
REncoder ICDE23	**BloomRF** EDBT23	**Grafite** SIGMOD24	**Oasis** VLDB24

Hot research topic in past decade

SuRF SIGMOD18	**Rosetta** SIGMOD2020	**SNARF** SIGMOD22	**Proteus** SIGMOD22
REncoder ICDE23	**BloomRF** EDBT23	**Grafite** SIGMOD24	**Oasis** VLDB24




SuRF
SIGMOD18

Rosetta
SIGMOD2020

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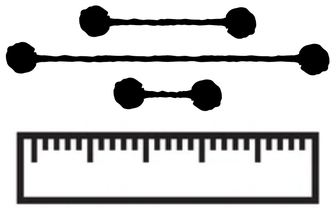

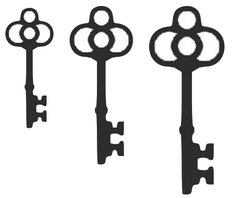

SuRF
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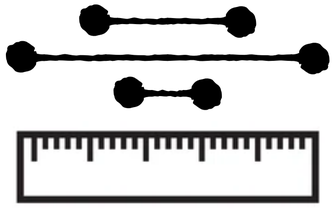
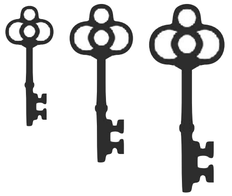


SuRF
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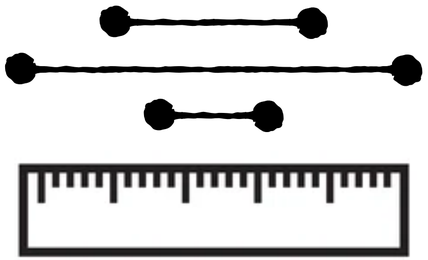
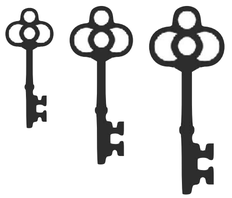


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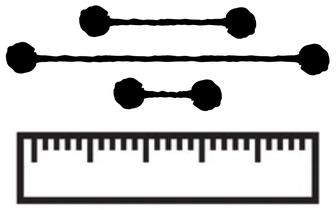
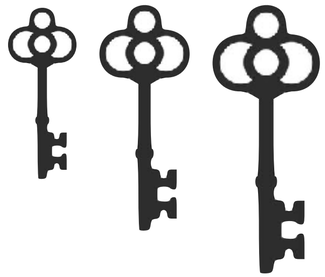


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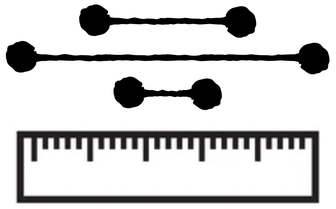

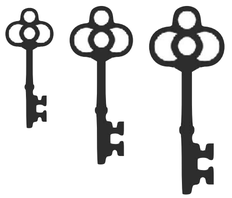

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BloomRF
EDBT23

Grafite
SIGMOD24

Oasis
VLDB24

None achieve all goals simultaneously

SuRF
SIGMOD18

Memento
SIGMOD24

Diva
VLDB25

SuRF
SIGMOD18

Me

Memento
SIGMOD24

Diva
VLDB25

SuRF
SIGMOD18

Memento
SIGMOD24

Diva
VLDB25

Navid

	SuRF	Memento	Diva
			
Var-length keys & queries			
FPR guarantee			
Query speed			
Dynamic			

	SuRF	Memento	Diva
			
Var-length keys & queries	Yes		
FPR guarantee	None		
Query speed	O(L) (L = key length)		
Dynamic	No		

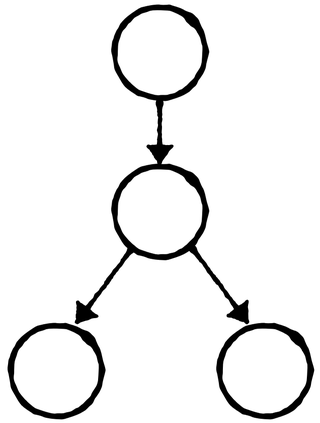
	SuRF	Memento	Diva
			
Var-length keys & queries	Yes	**No**	
FPR guarantee	None	**Robust**	
Query speed	O(L) (L = key length)	**O(1)**	
Dynamic	No	**Yes**	

	SuRF	Memento	Diva
			
Var-length keys & queries	Yes	No	**Yes**
FPR guarantee	None	Robust	**Semi-Robust**
Query speed	O(L) (L = key length)	O(1)	**O(log L)**
Dynamic	No	Yes	**Yes**

SuRF: Practical Range Query Filtering with Fast Succinct Tries

Huanchen Zhang, Hyeontaek Lim, Viktor Leis, David G. Andersen,
Michael Kaminsky, Kimberly Keeton, Andrew Pavlo

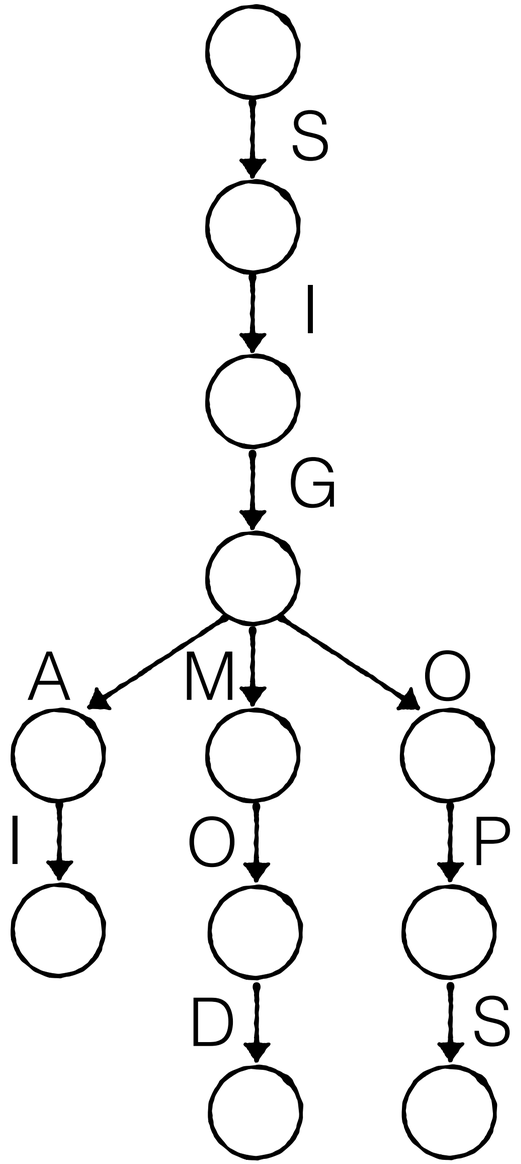
SIGMOD18



Starting Point

Keys

SIGAI
SIGMOD
SIGOPS



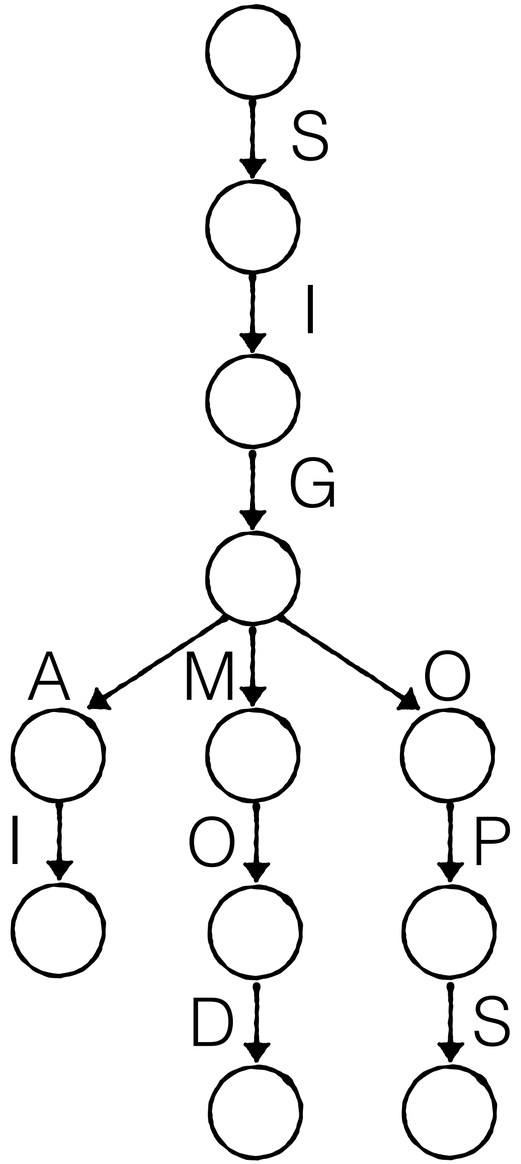
Starting Point

Keys

SIGAI

SIGMOD

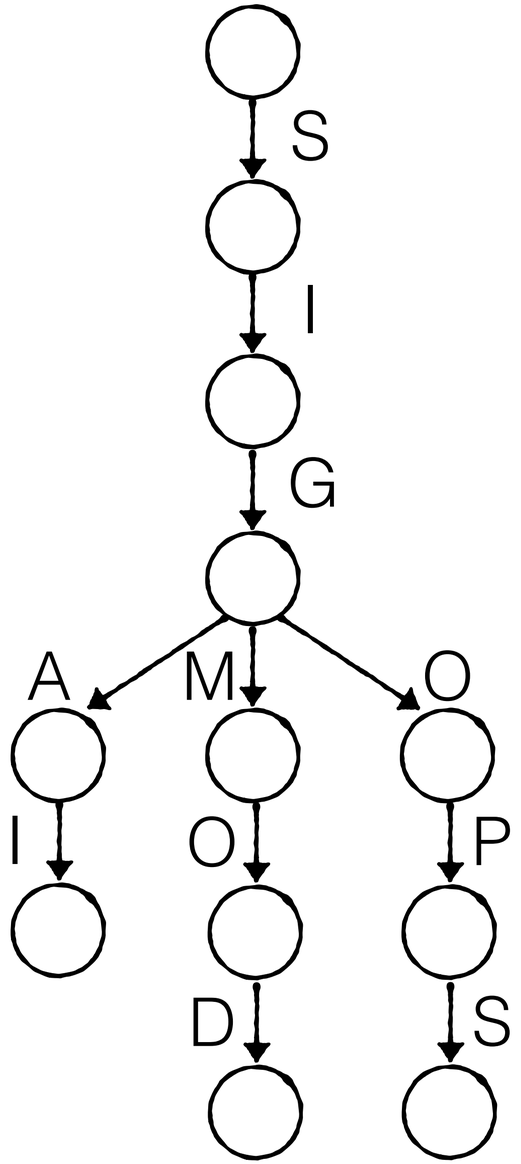
SIGOPS



Fanout - 256

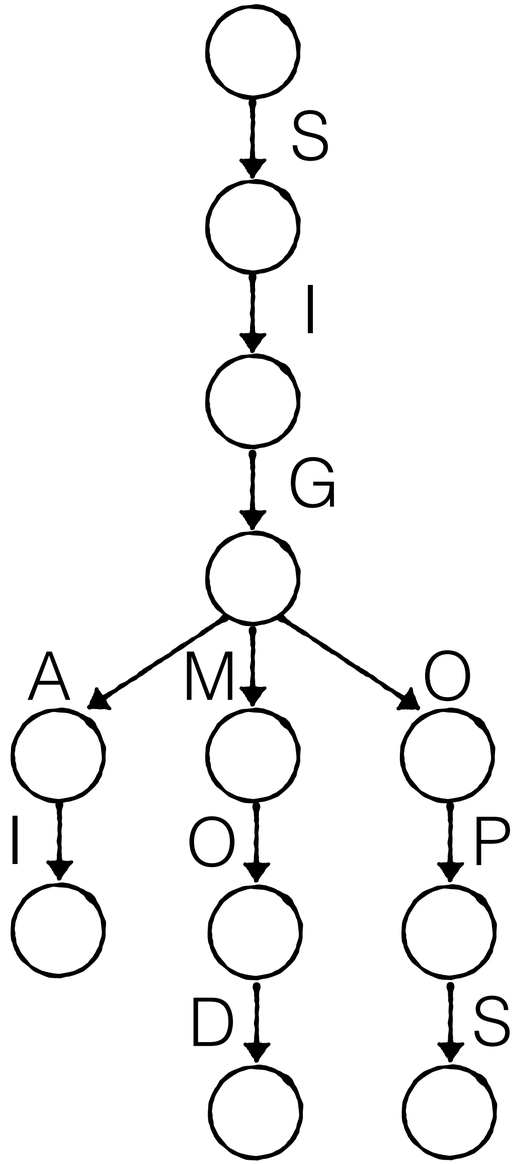
(1 byte)

Problems?



Problems?

1. Stores full keys



Problems?

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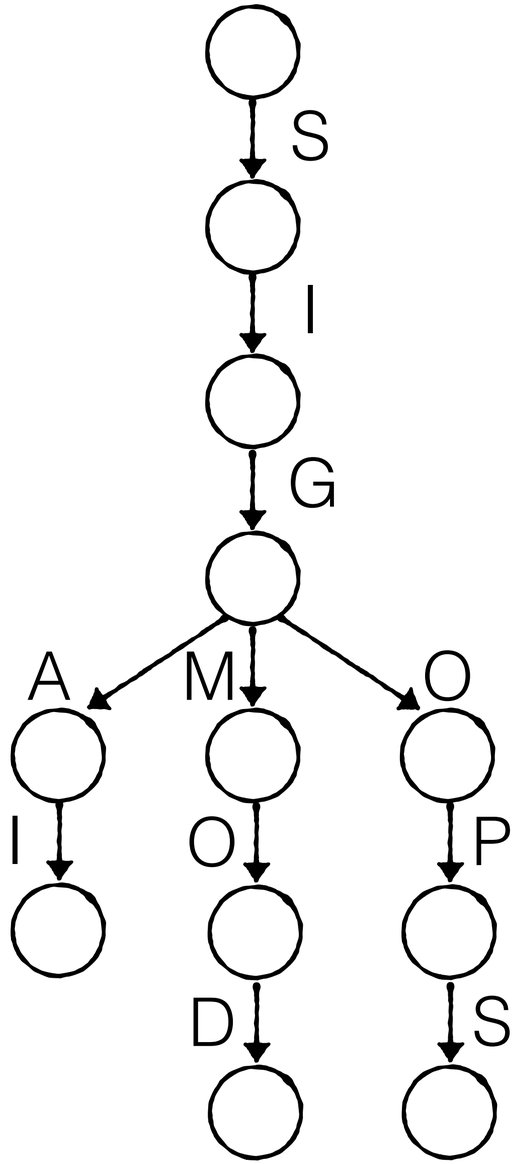
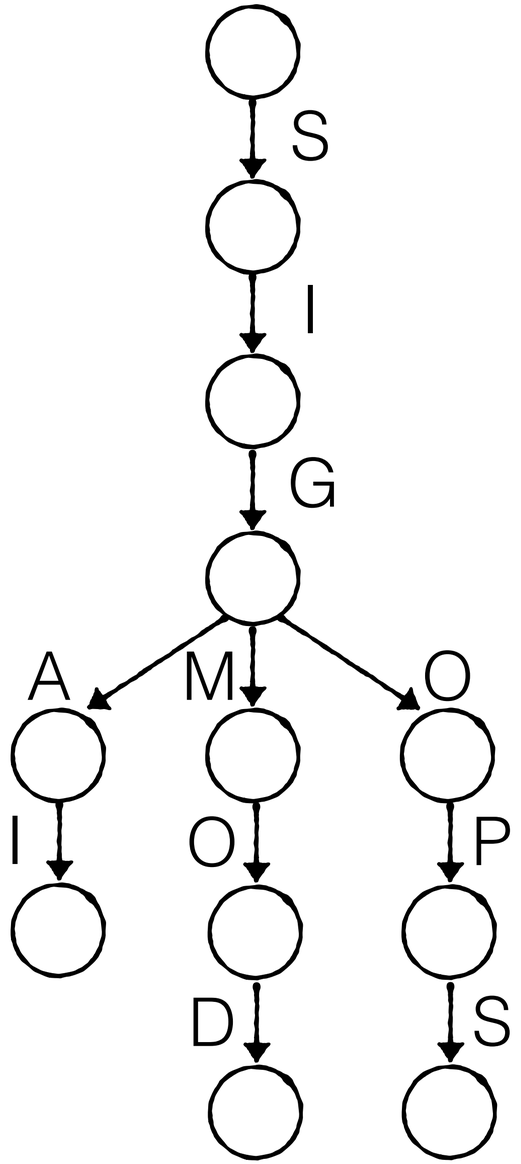


2. Pointers take space

1. Stores full keys

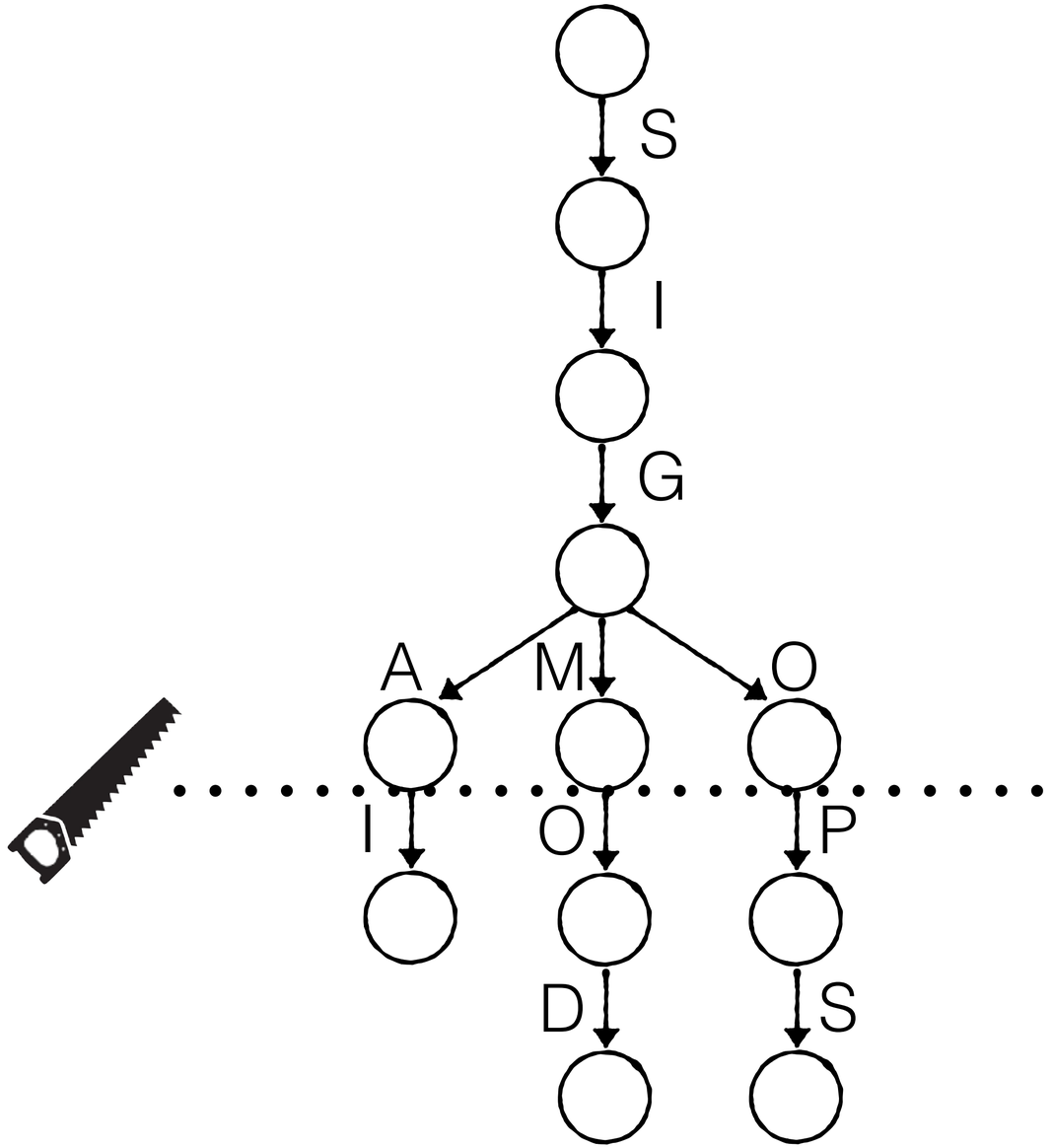
truncation



2. Pointers take space

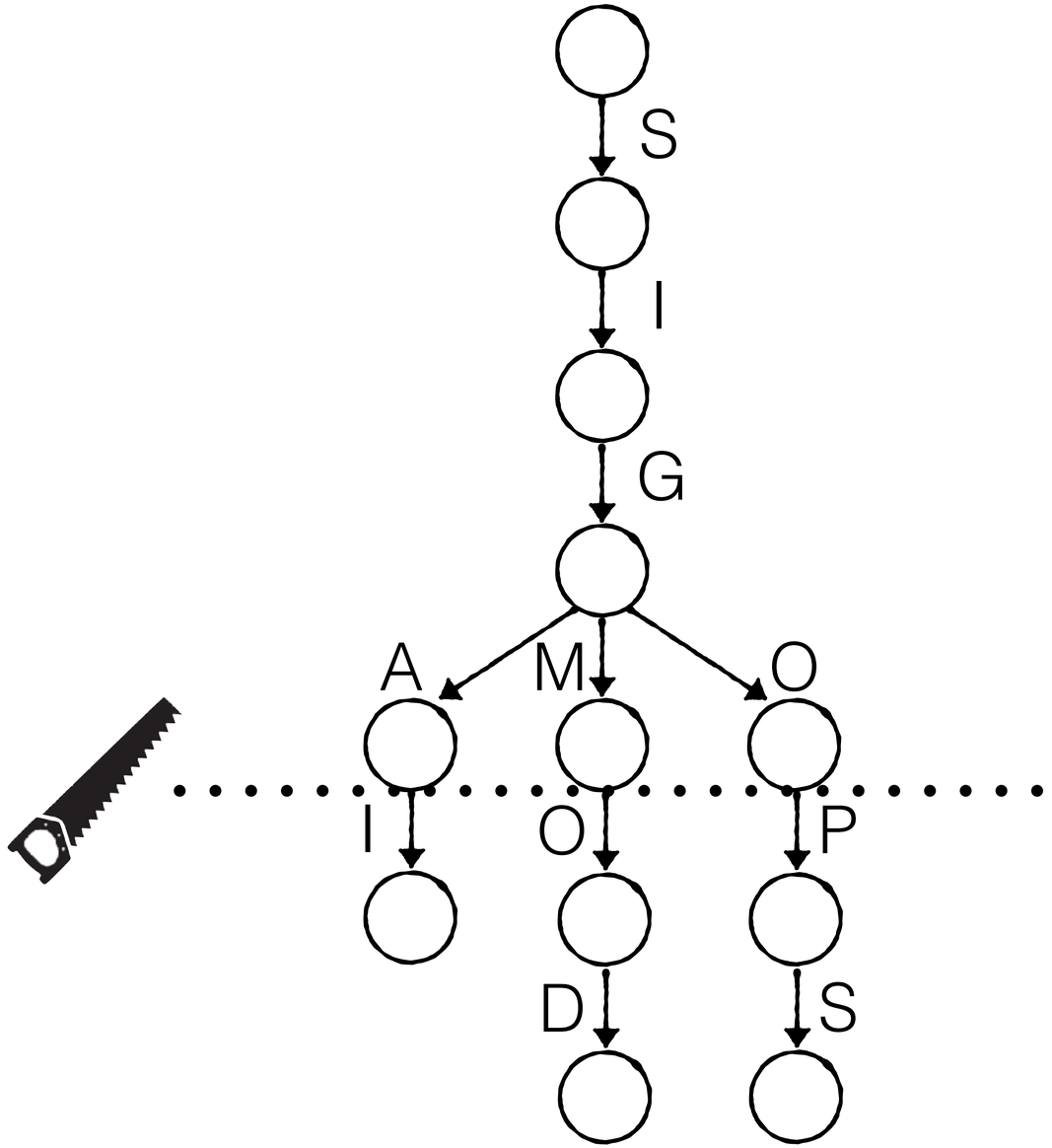
Succinct encoding

truncation

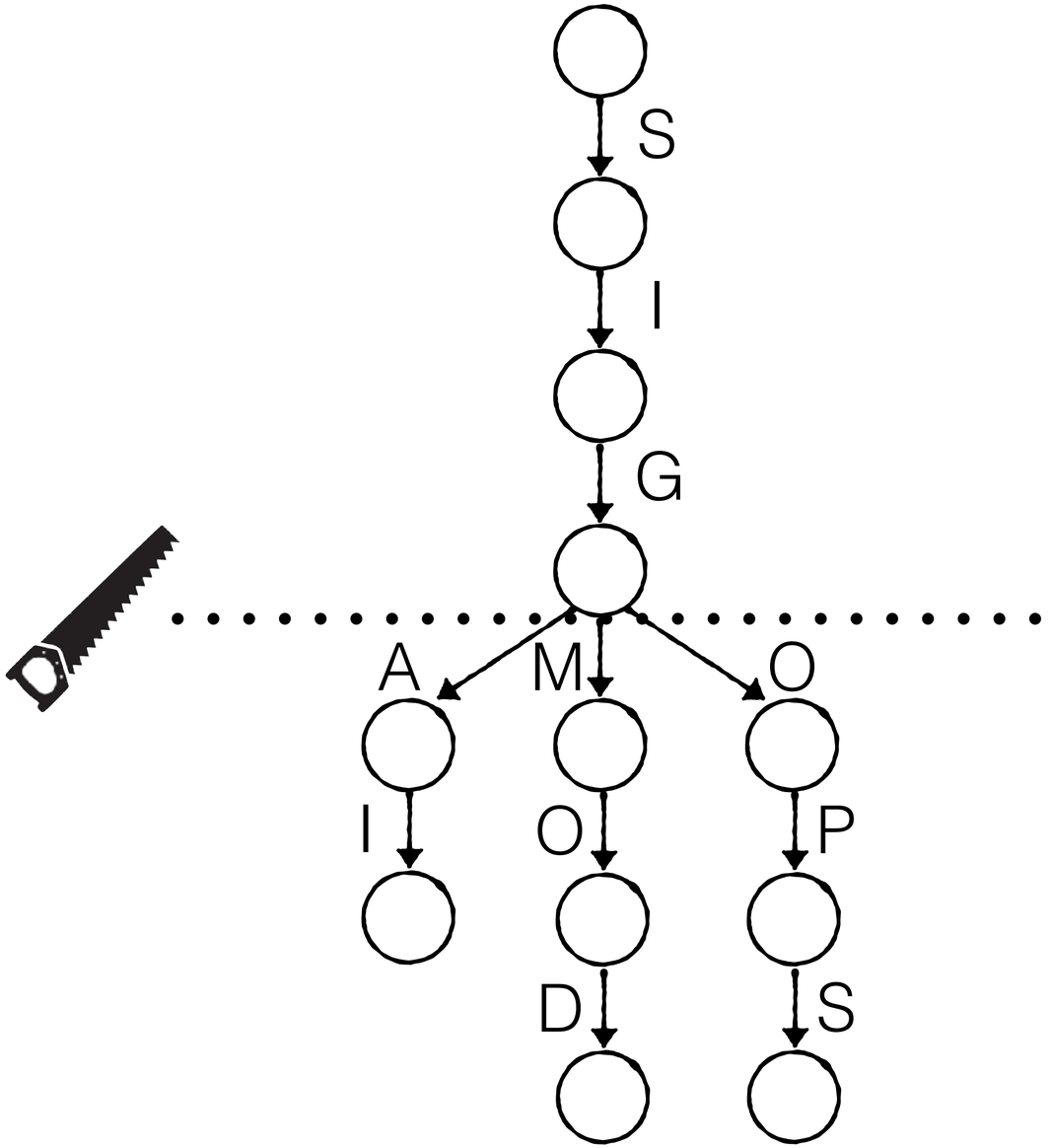


Keep at least one unique byte for each key

truncation

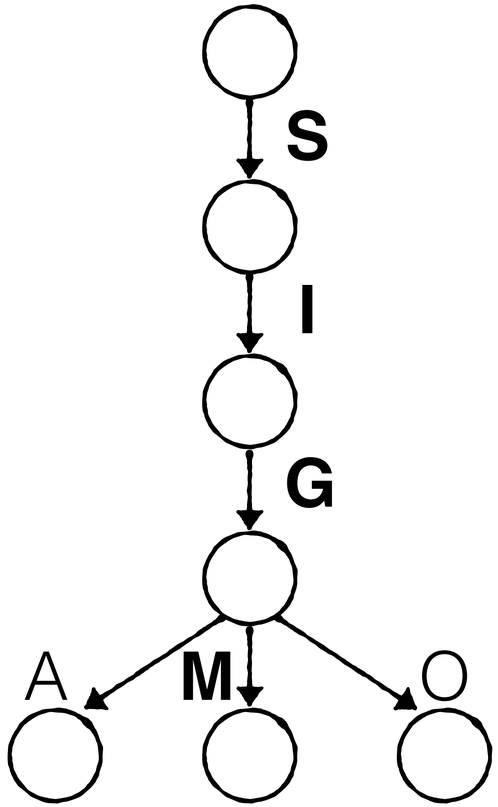


Keep at least one unique byte for each key



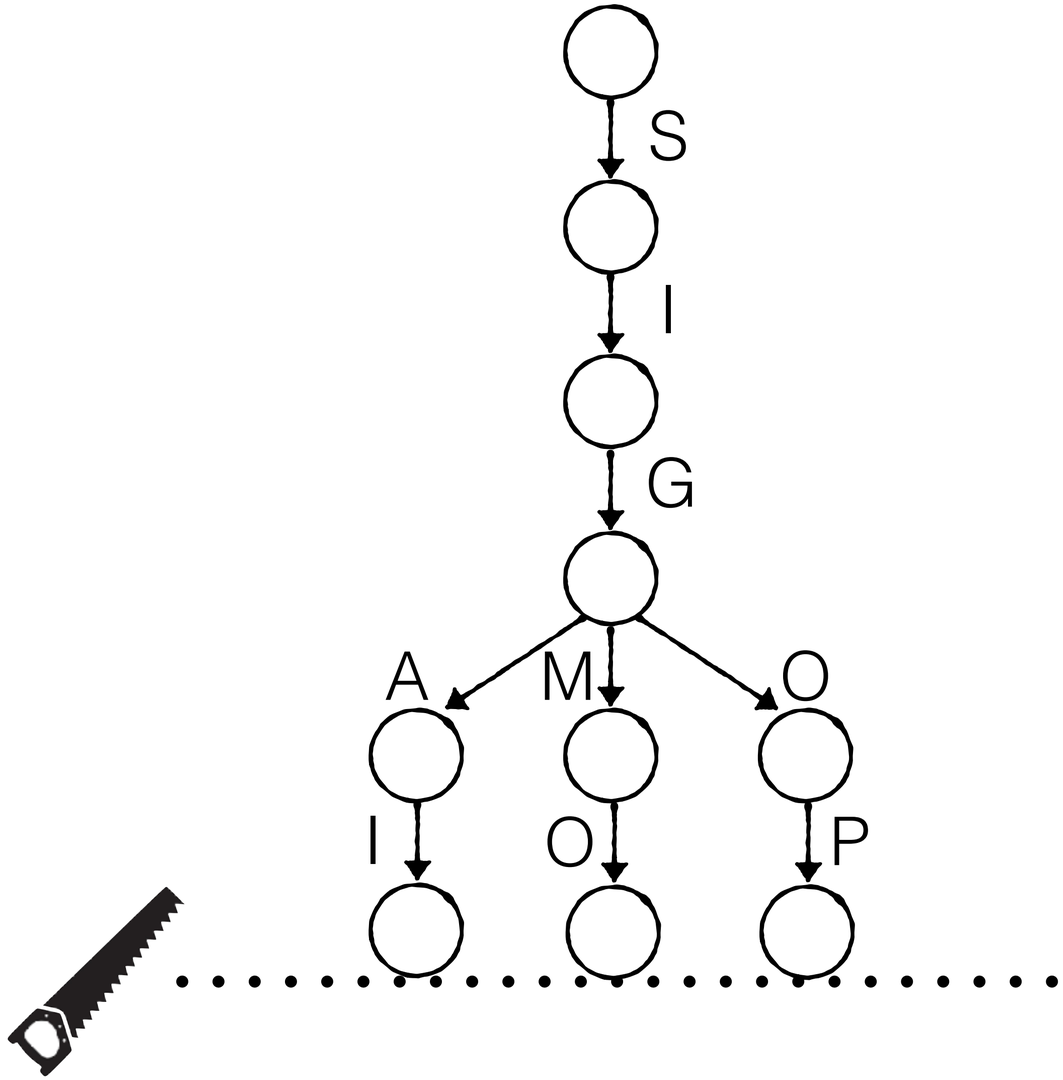
Not permitted

We now get false positives (e.g., query SIGMETRICS)



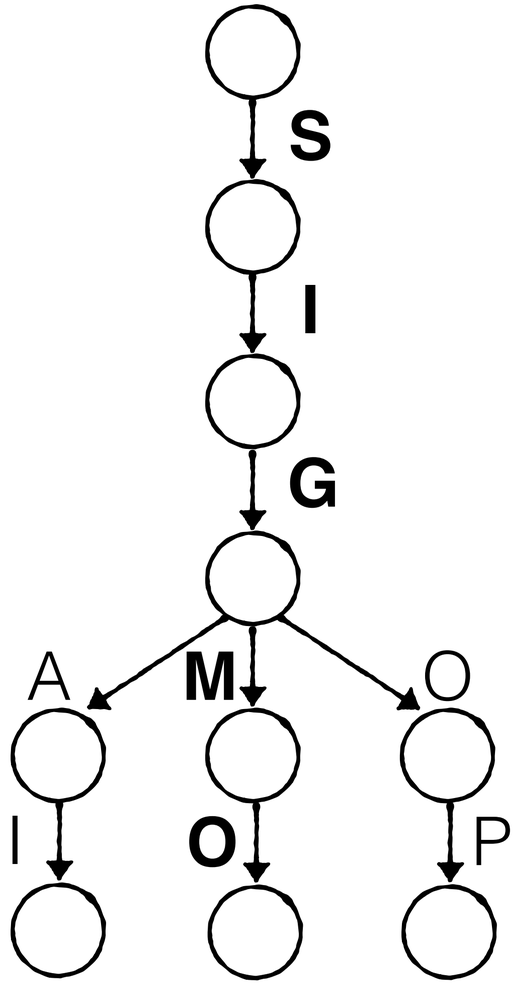
Match

We now get false positives (e.g., query SIGMETRICS)



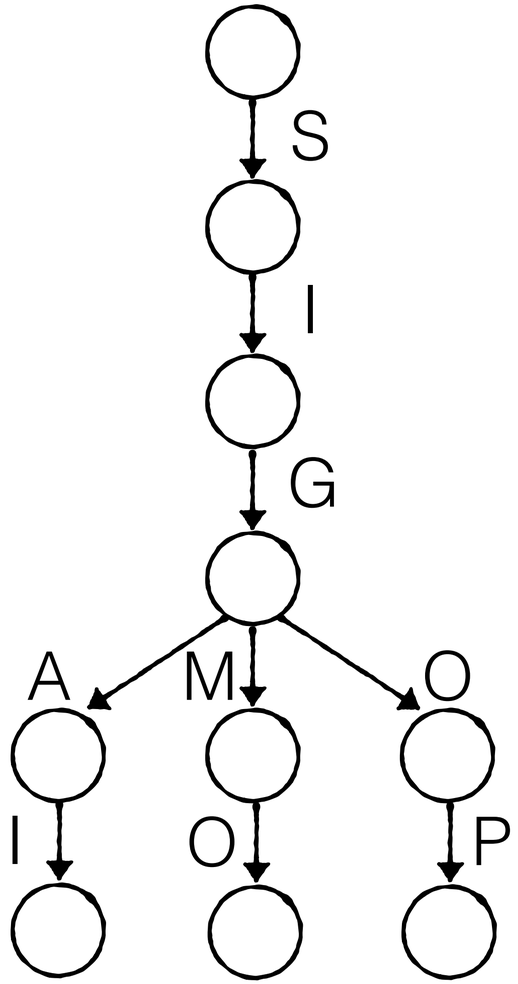
Can truncate later - better FPR, worse space

We now get false positives (e.g., query **SIGMETRICS**)

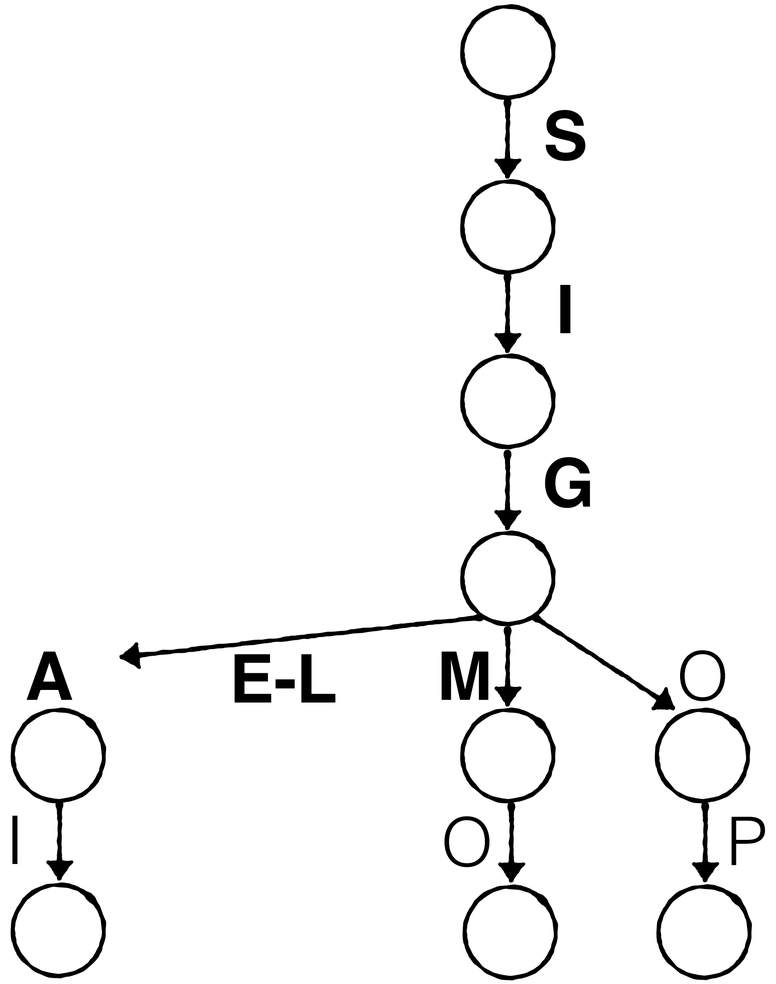


Negative :)

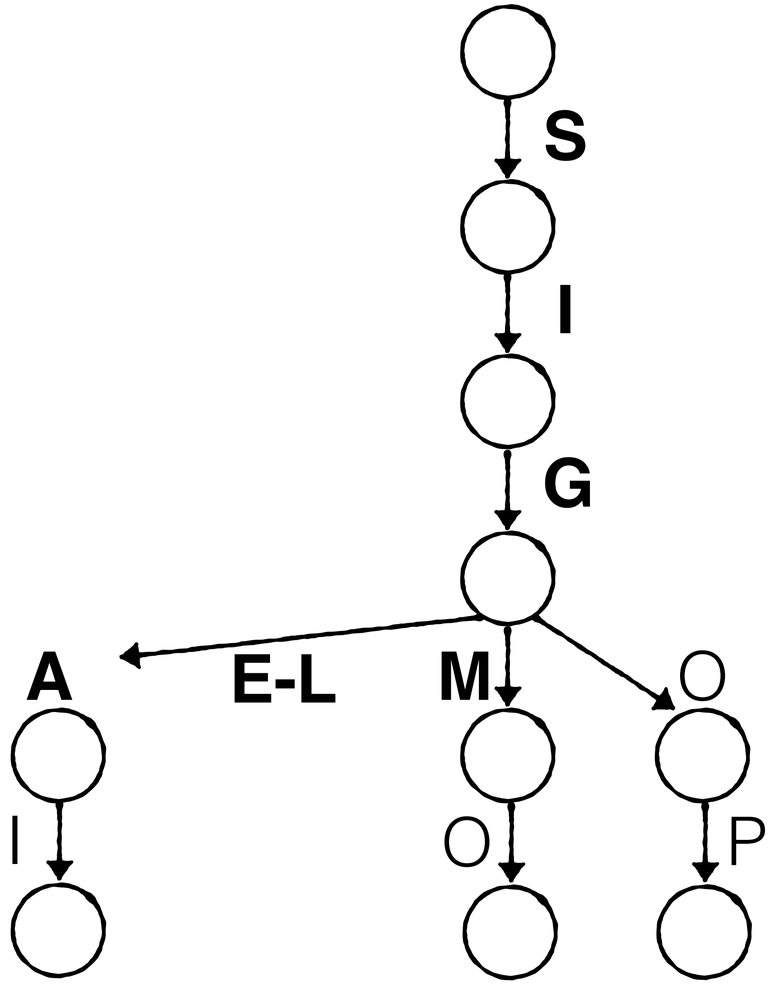
Range query: SIGE - SIGL



Range query: SIG**E -** SIG**L**

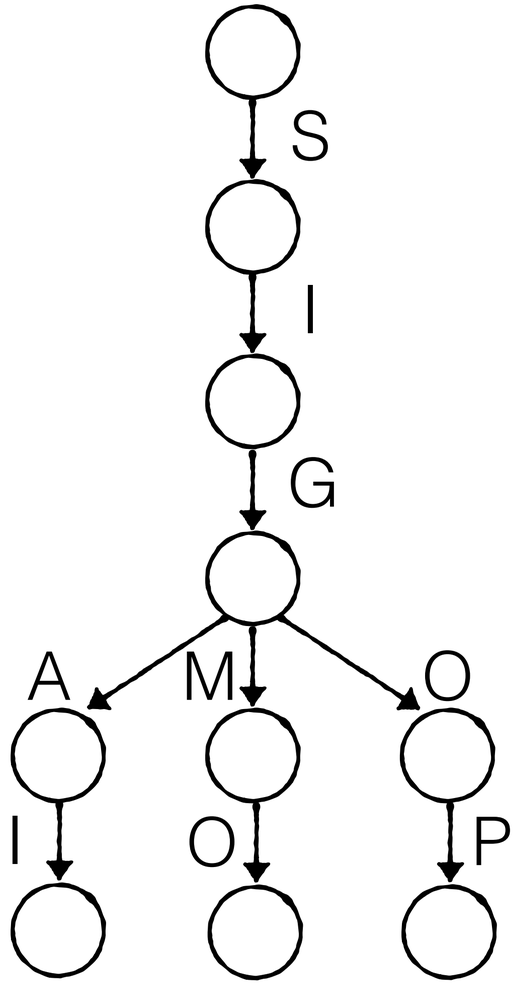


Range query: SIG**E -** SIG**L**

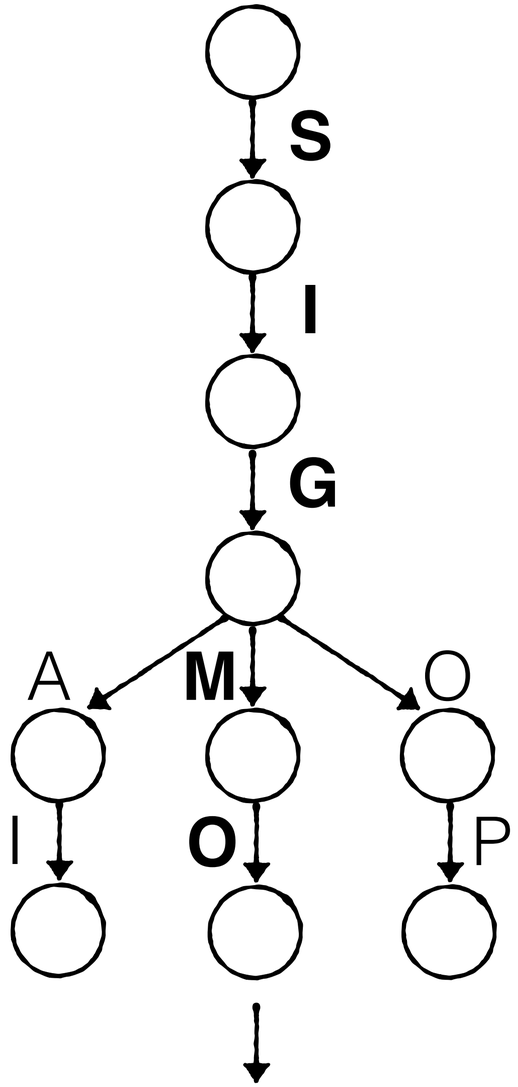


Negative :)

Range query: **SIGMOR - SIGMOS**

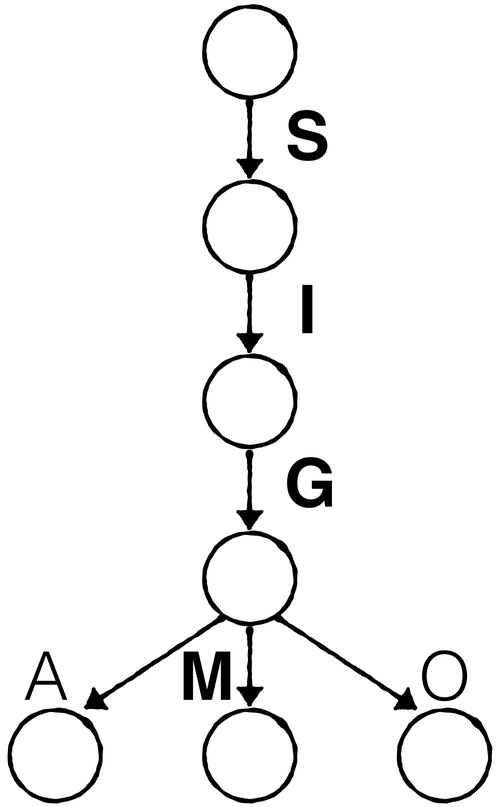


Range query: **SIGMOR - SIGMOS**



R-S? **False positive**

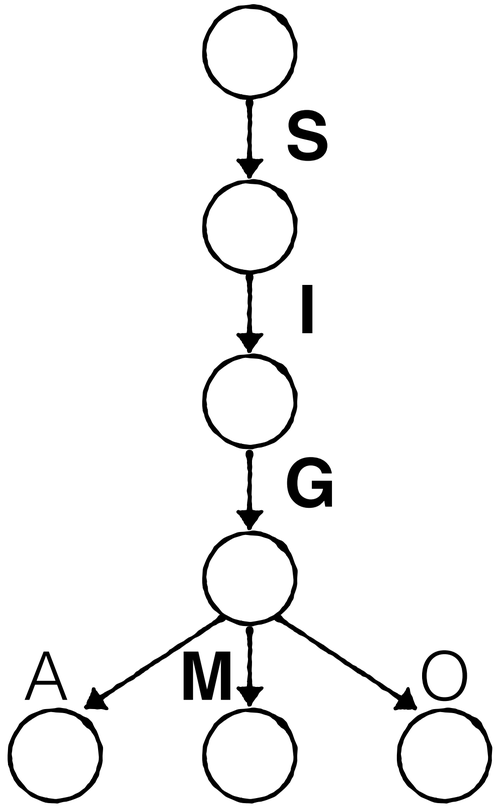
If many queries match existing prefixes, the FPR increases



e.g., **SIGMA**

SIGMOID

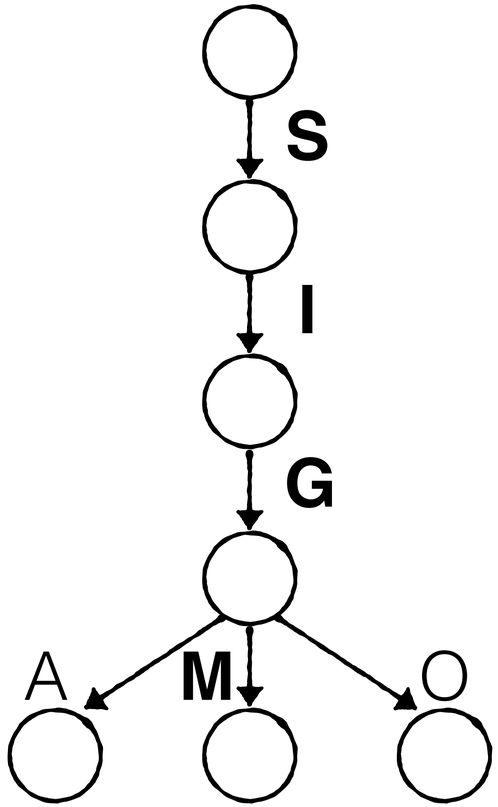
If many queries match existing prefixes, the FPR increases



e.g., SIGMA
SIGMOID

Correlated Workload

If many queries match existing prefixes, the FPR increases

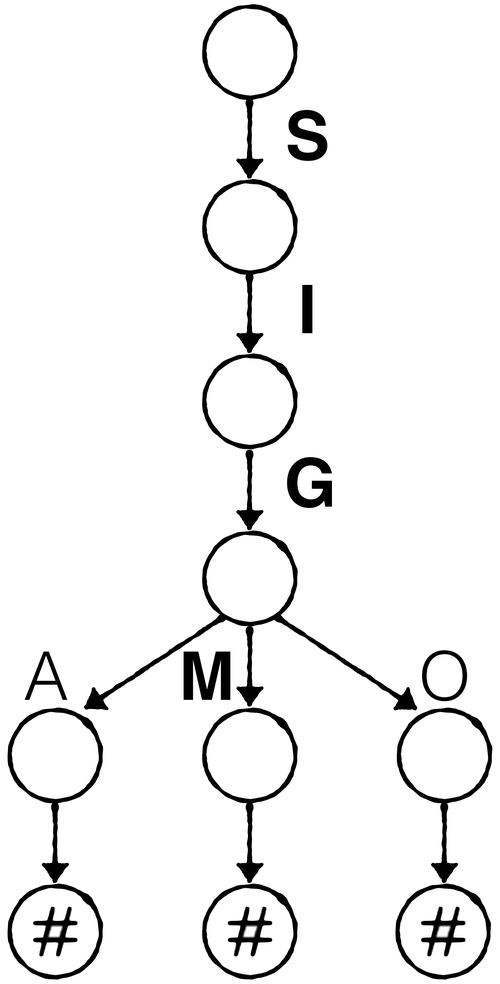


e.g., SIGMA
SIGMOID

Correlated Workload

Can we alleviate this problem for point queries?

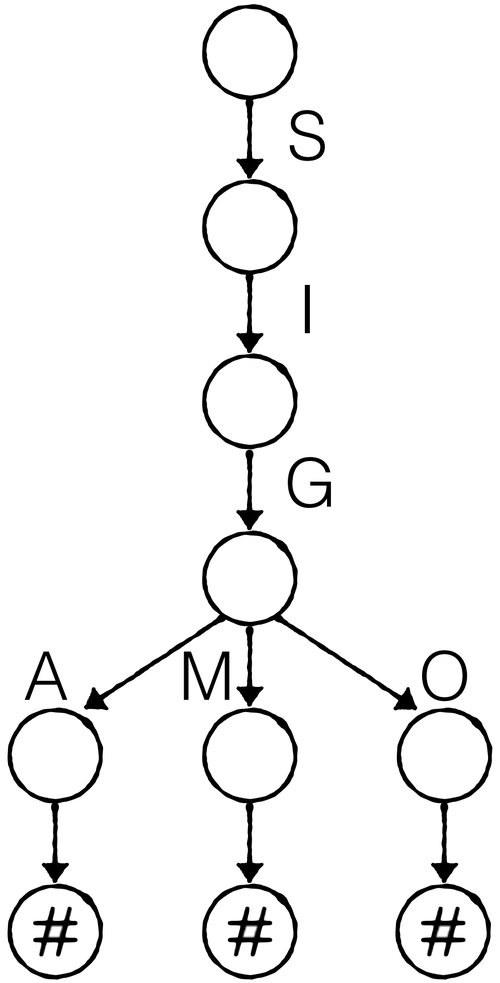
If many queries match existing prefixes, the FPR increases

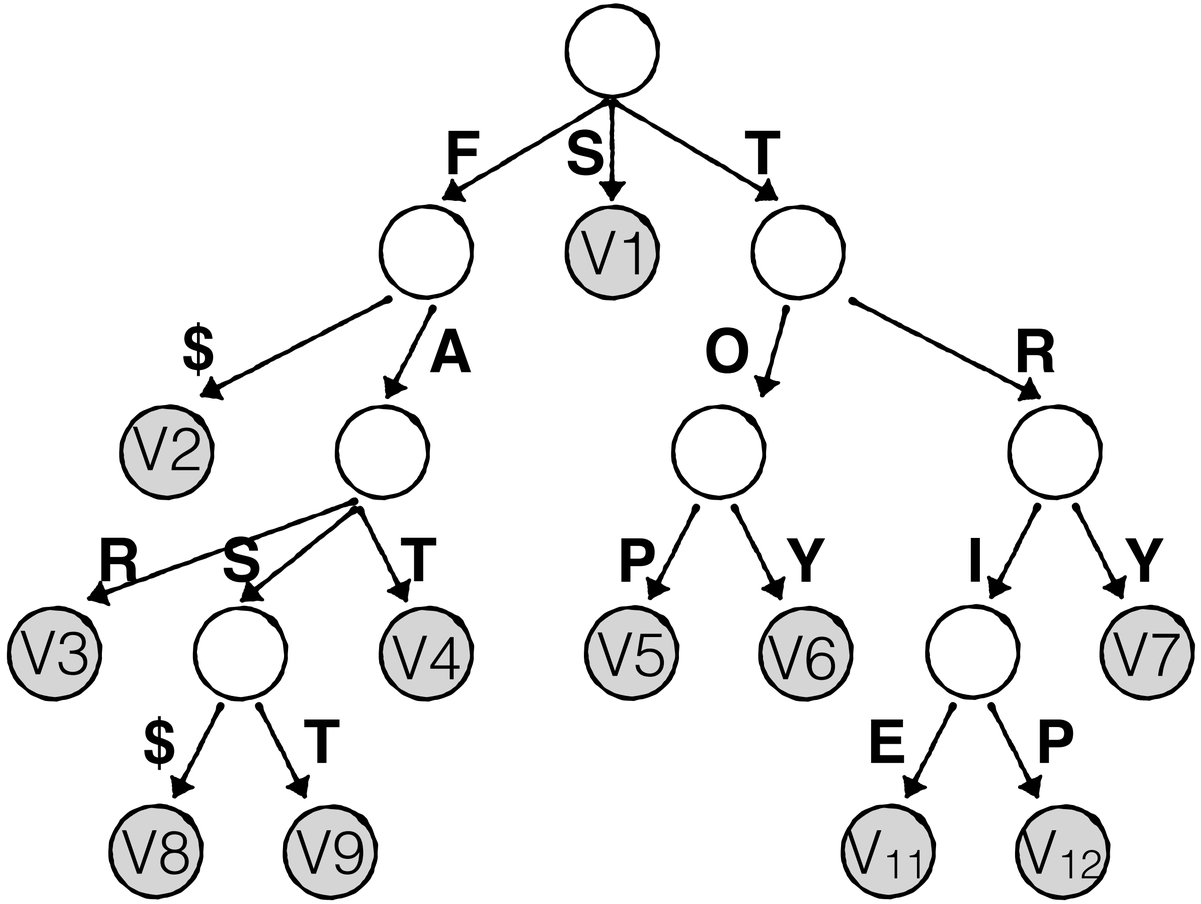


e.g., SIGMA
SIGMOID

Can we alleviate this problem for point queries? **Add 1 byte hash**

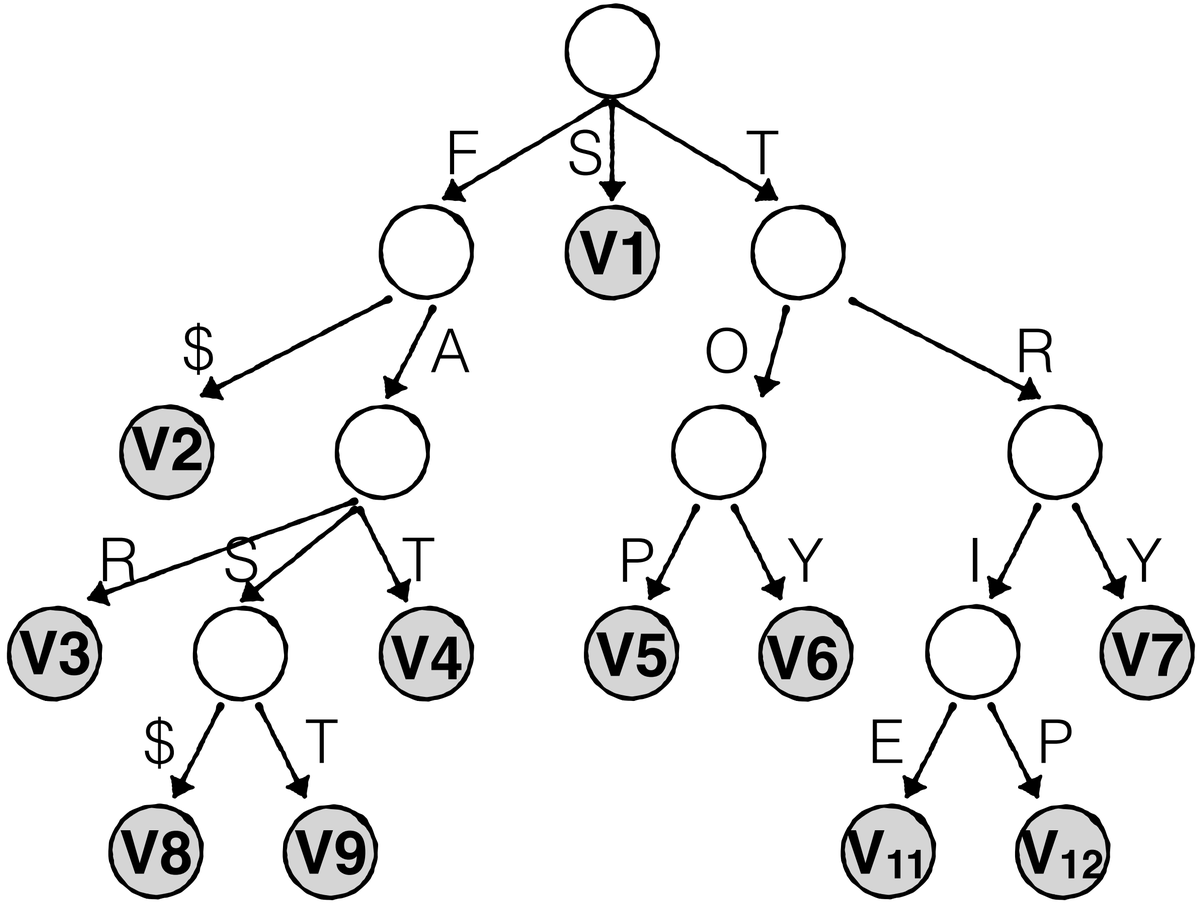
How to encode trie logically?





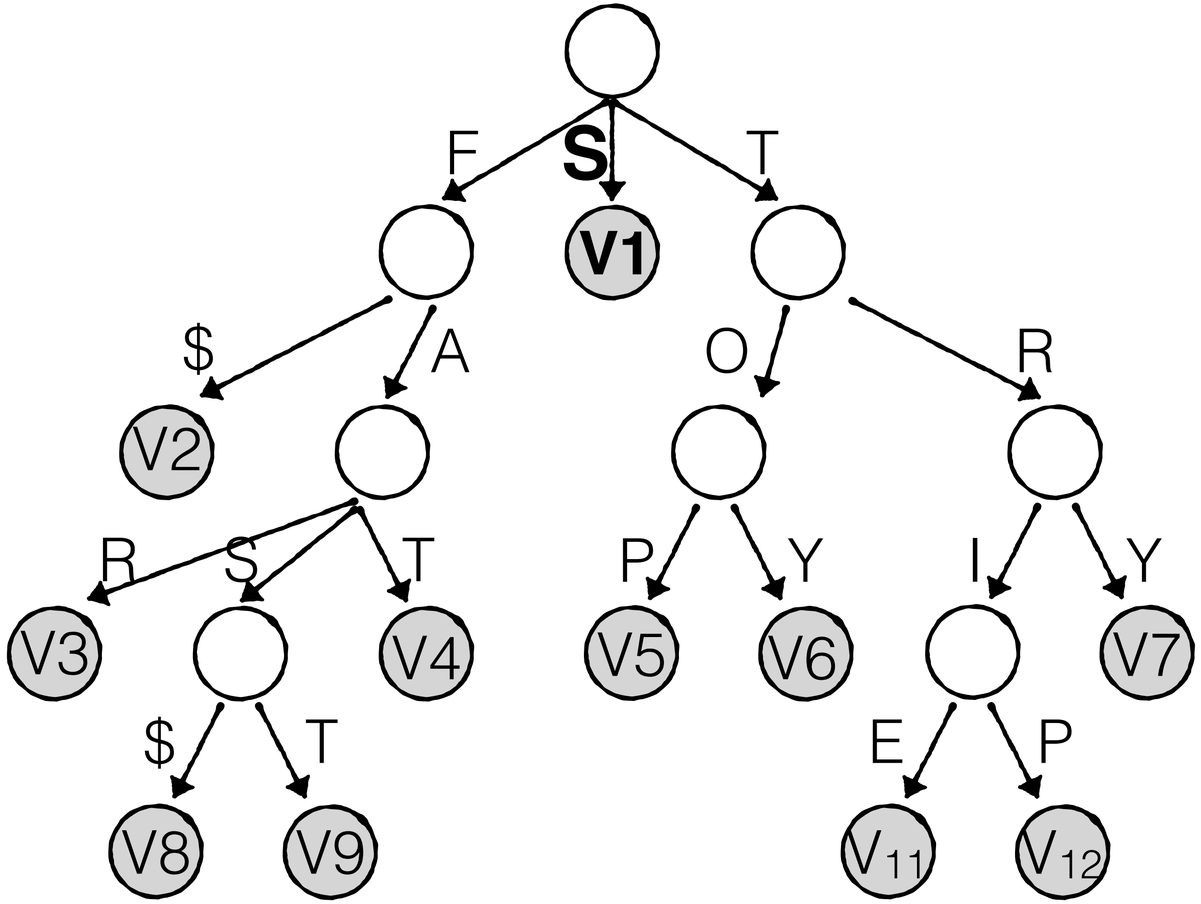
F, FAR, FAS, FAST, FAT, S, TOP, TOY, TRIE, TRIP, TRY

Each key leads to leaf payload (e.g., pointer and/or hash)



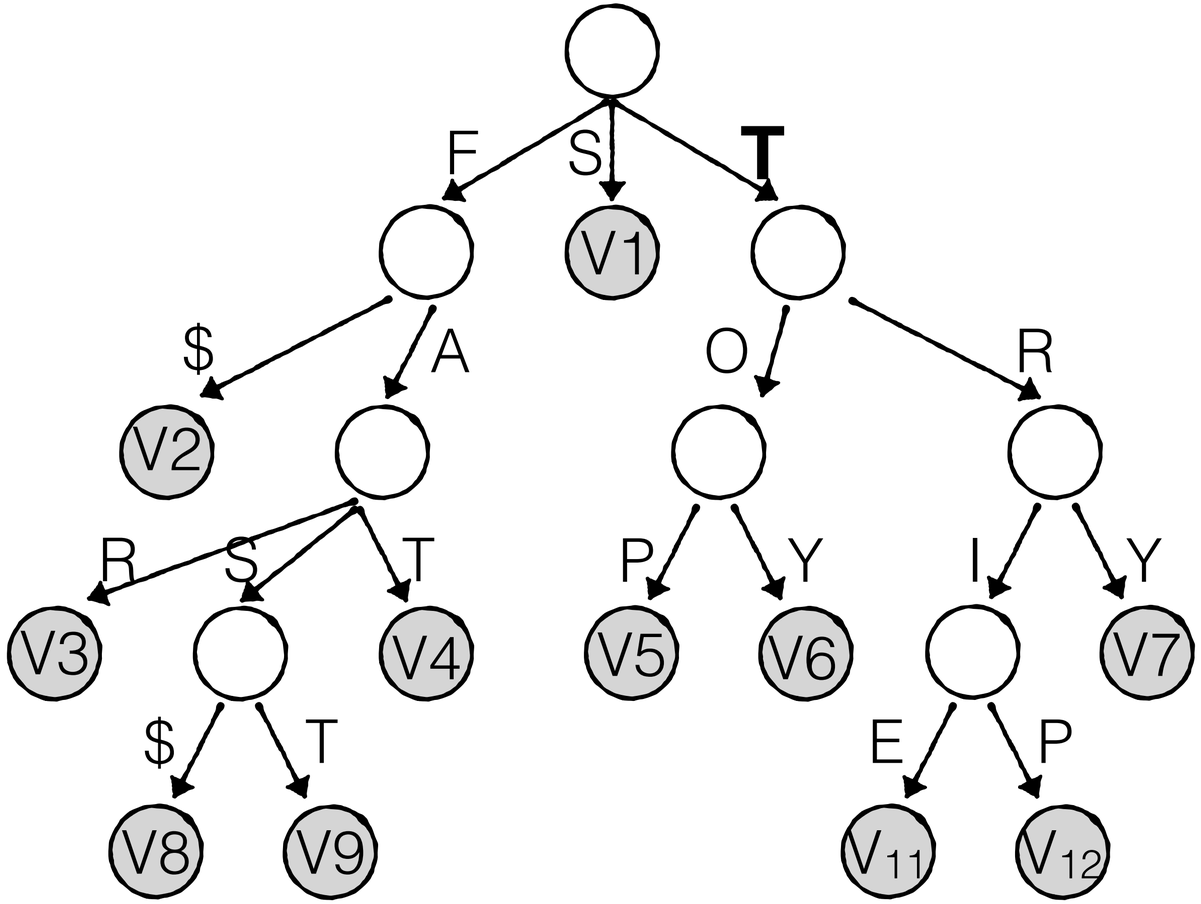
F, FAR, FAS, FAST, FAT, S, TOP, TOY, TRIE, TRIP, TRY

S leads to leaf: **full key**
not prefix of any other key



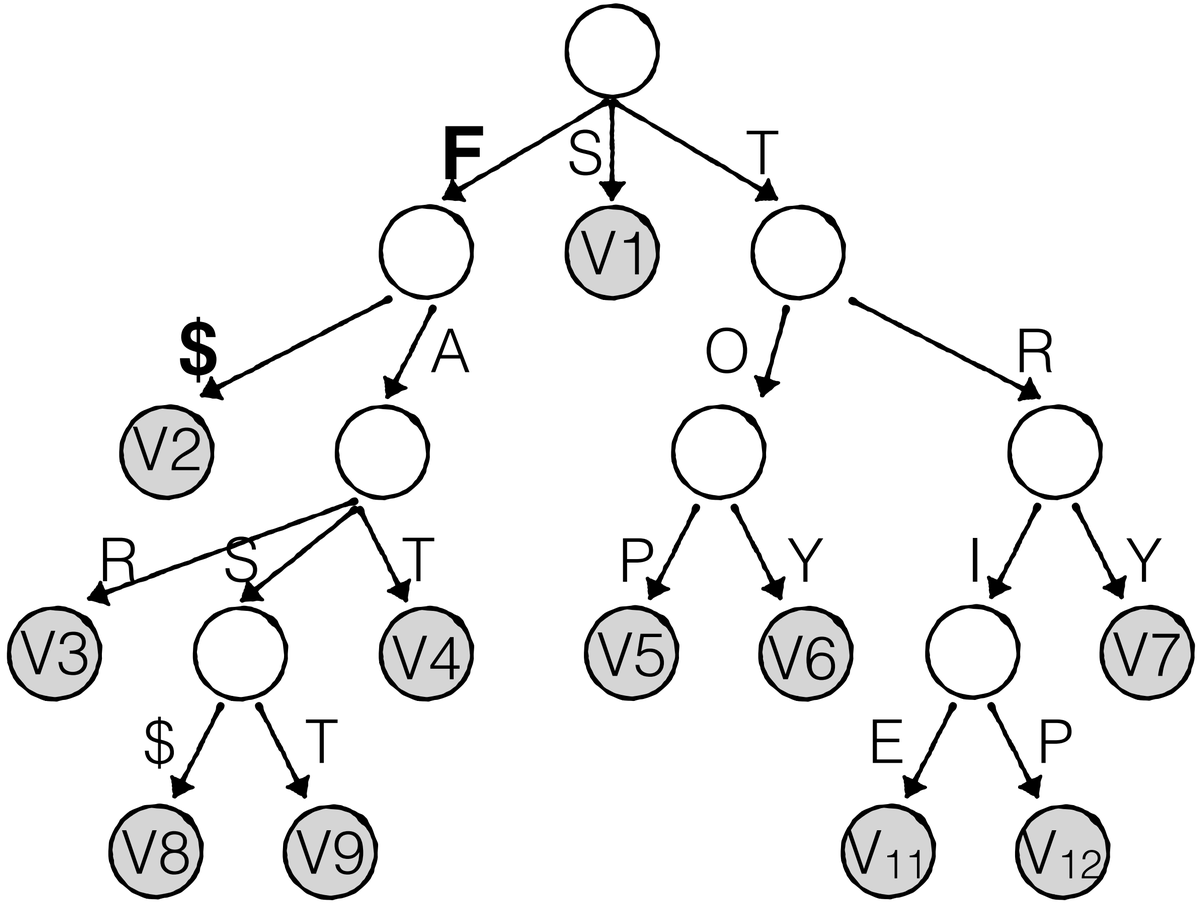
F, FAR, FAS, FAST, FAT, **S**, TOP, TOY, TRIE, TRIP, TRY

T leads to internal node: **not full key**
prefix of one or more other keys



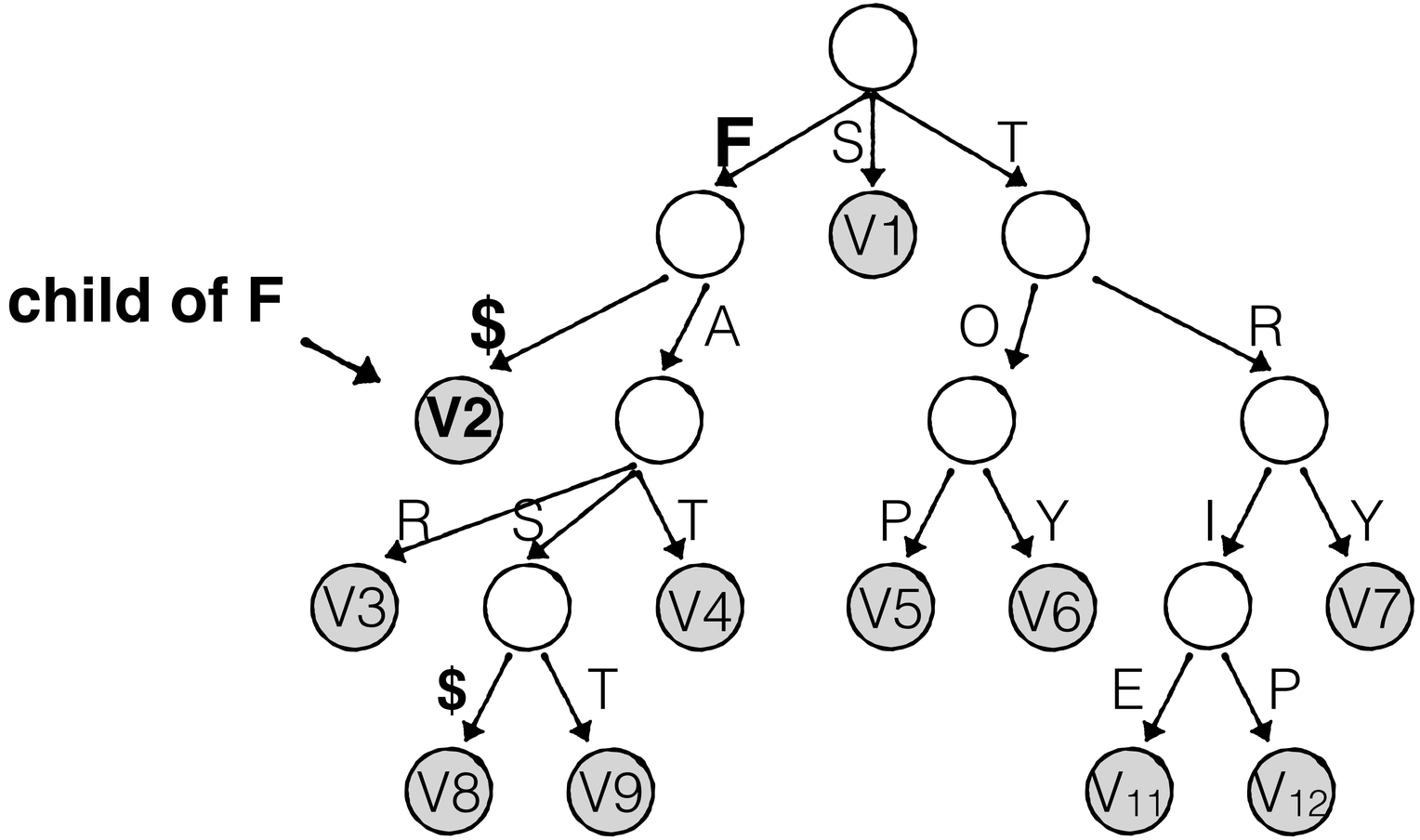
F, FAR, FAS, FAST, FAT, S, **T**OP, **T**OY, **T**RIE, **T**RIP, **T**RY

F leads to internal node with $ child: **full key**
prefix of one or more other keys



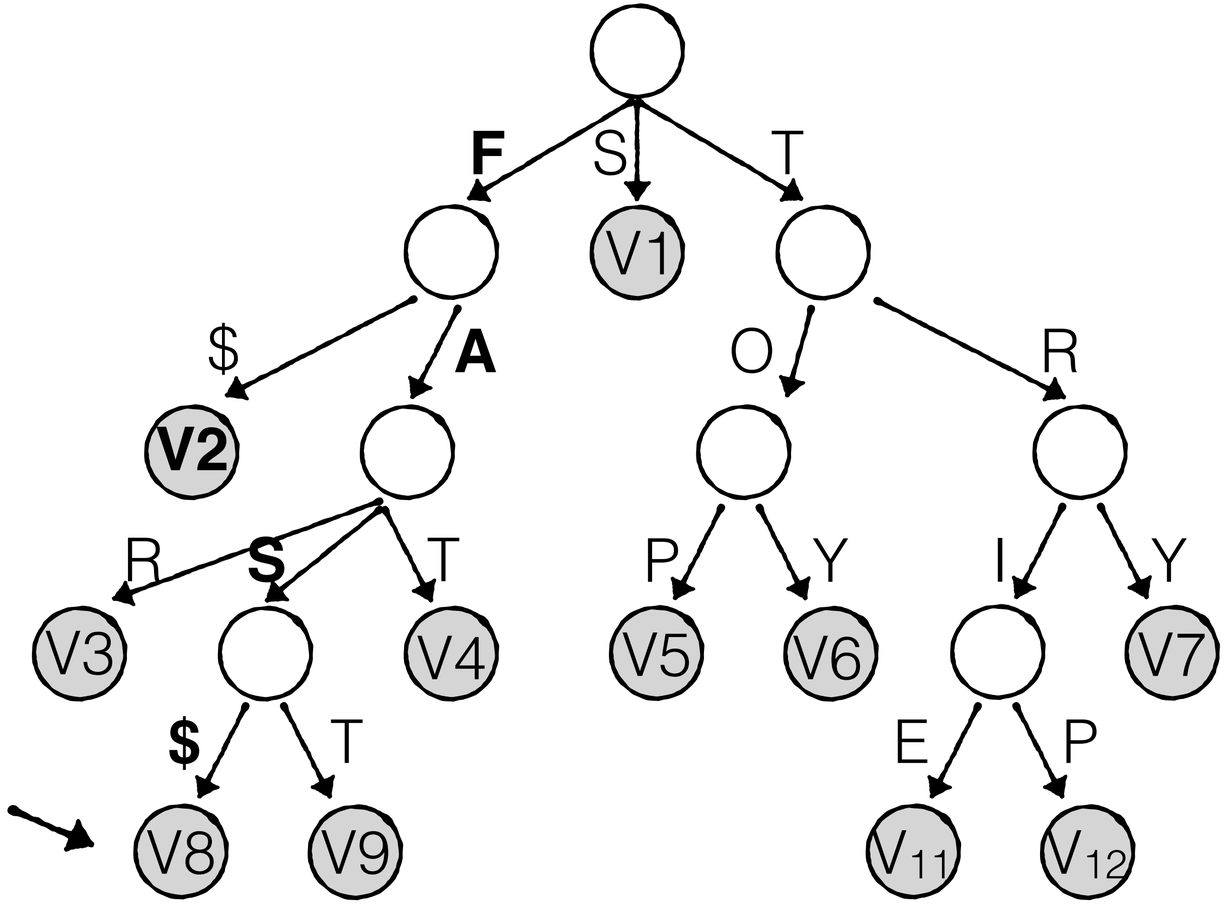
F, **F**AR, **F**AS, **F**AST, **F**AT, S, TOP, TOY, TRIE, TRIP, TRY

F leads to internal node with $ child: full key
prefix of one or more other keys



F, **F**AR, **F**AS, **F**AST, **F**AT, S, TOP, TOY, TRIE, TRIP, TRY

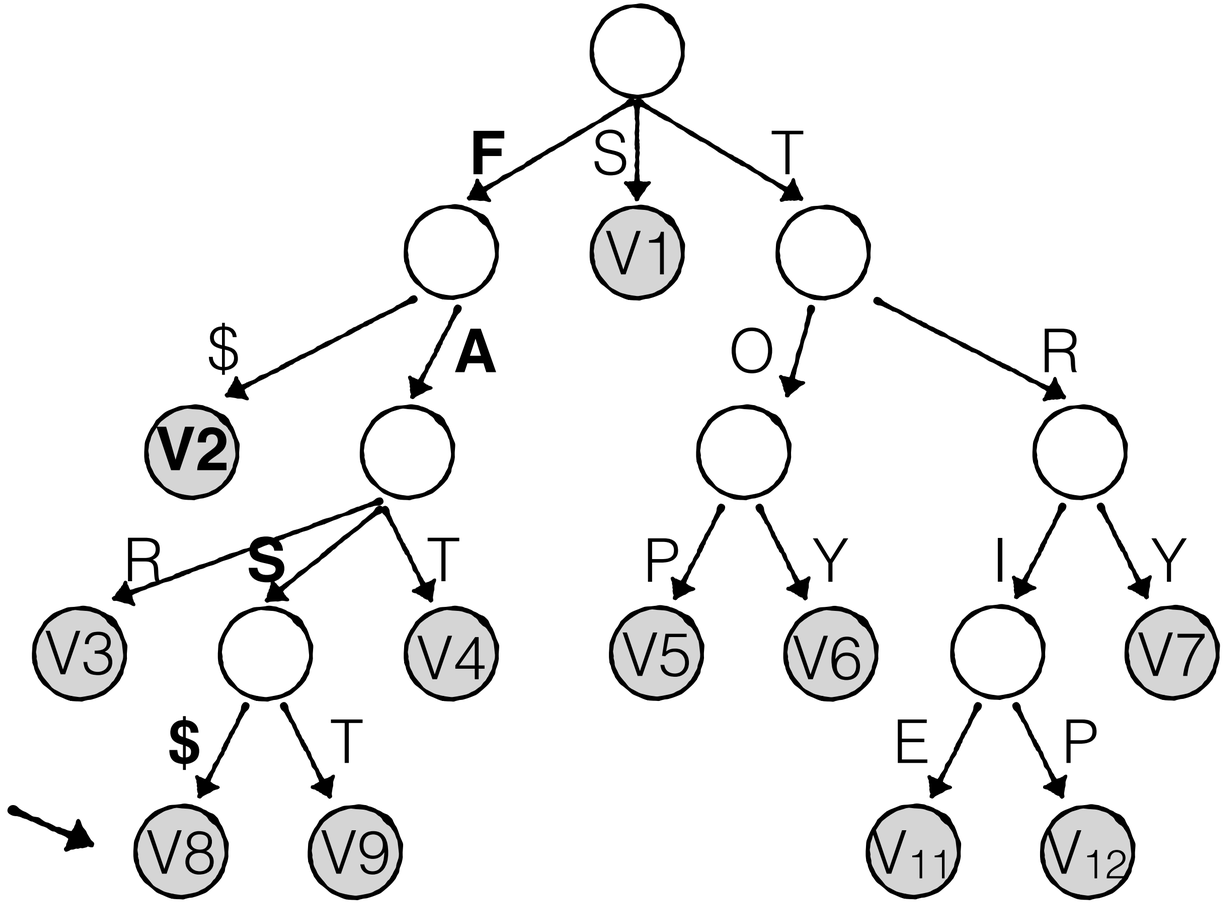
FAS leads to internal node with $ child: full key
prefix of one or more other keys



child of FAS

F, FAR, **FAS**, FAST, FAT, S, TOP, TOY, TRIE, TRIP, TRY

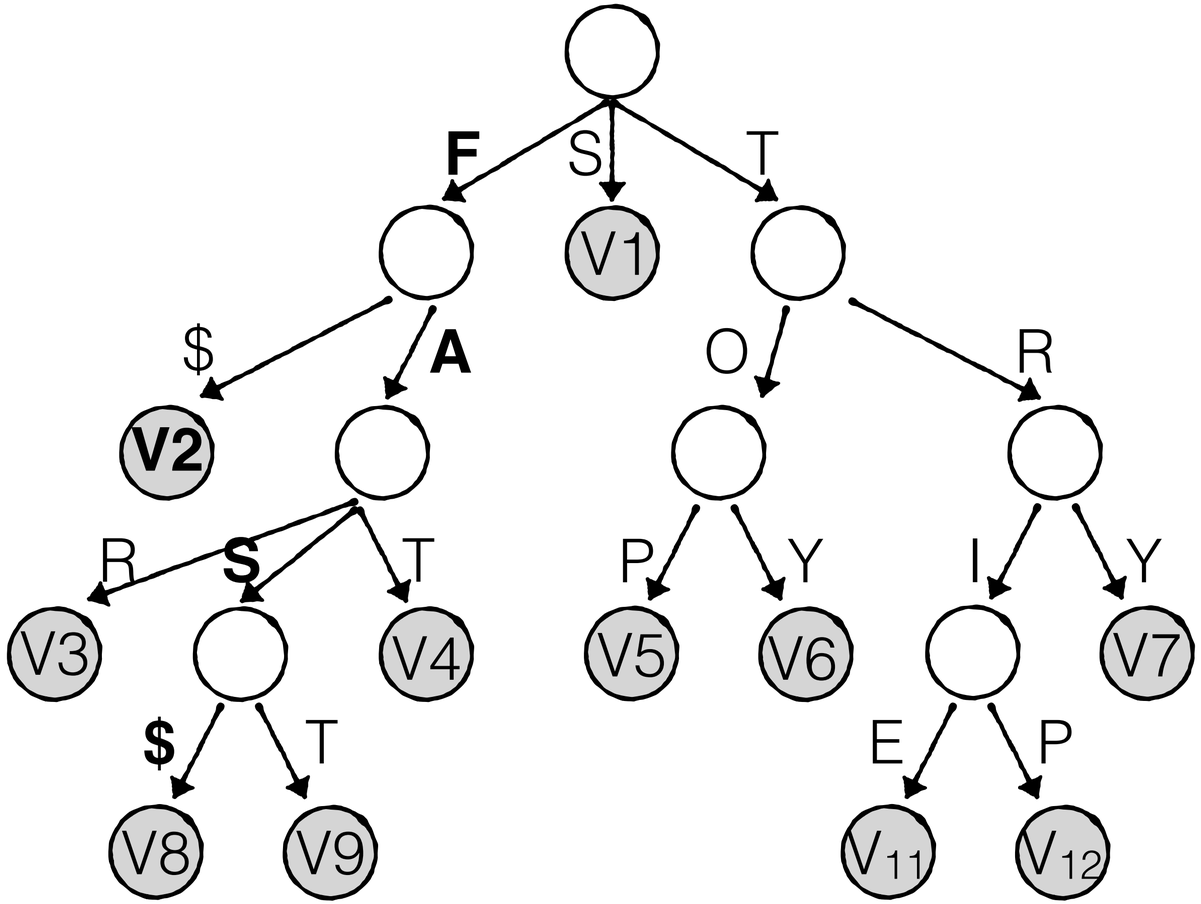
A prefix is always represented by an internal node



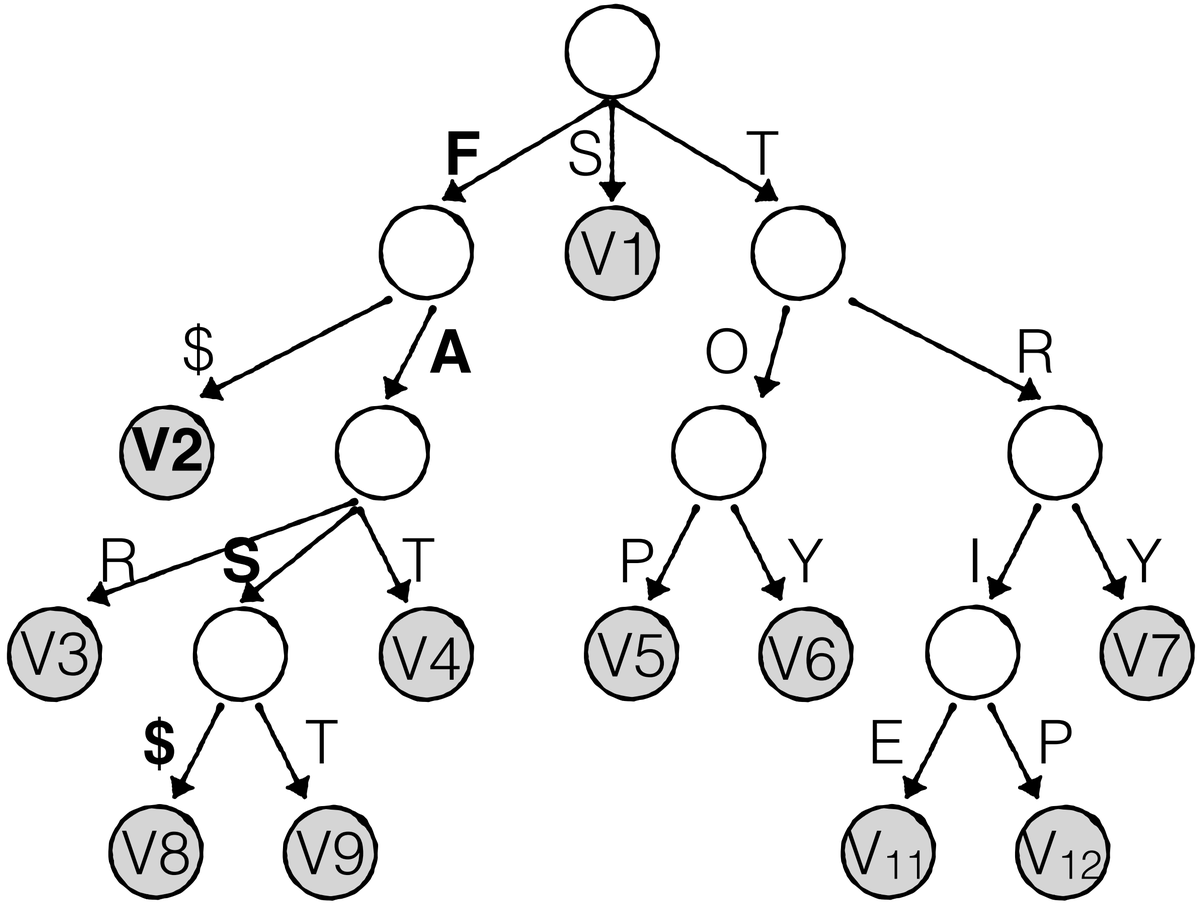
child of FAS

F, FAR, **FAS**, FAST, FAT, S, TOP, TOY, TRIE, TRIP, TRY

How to encode physically and succinctly?

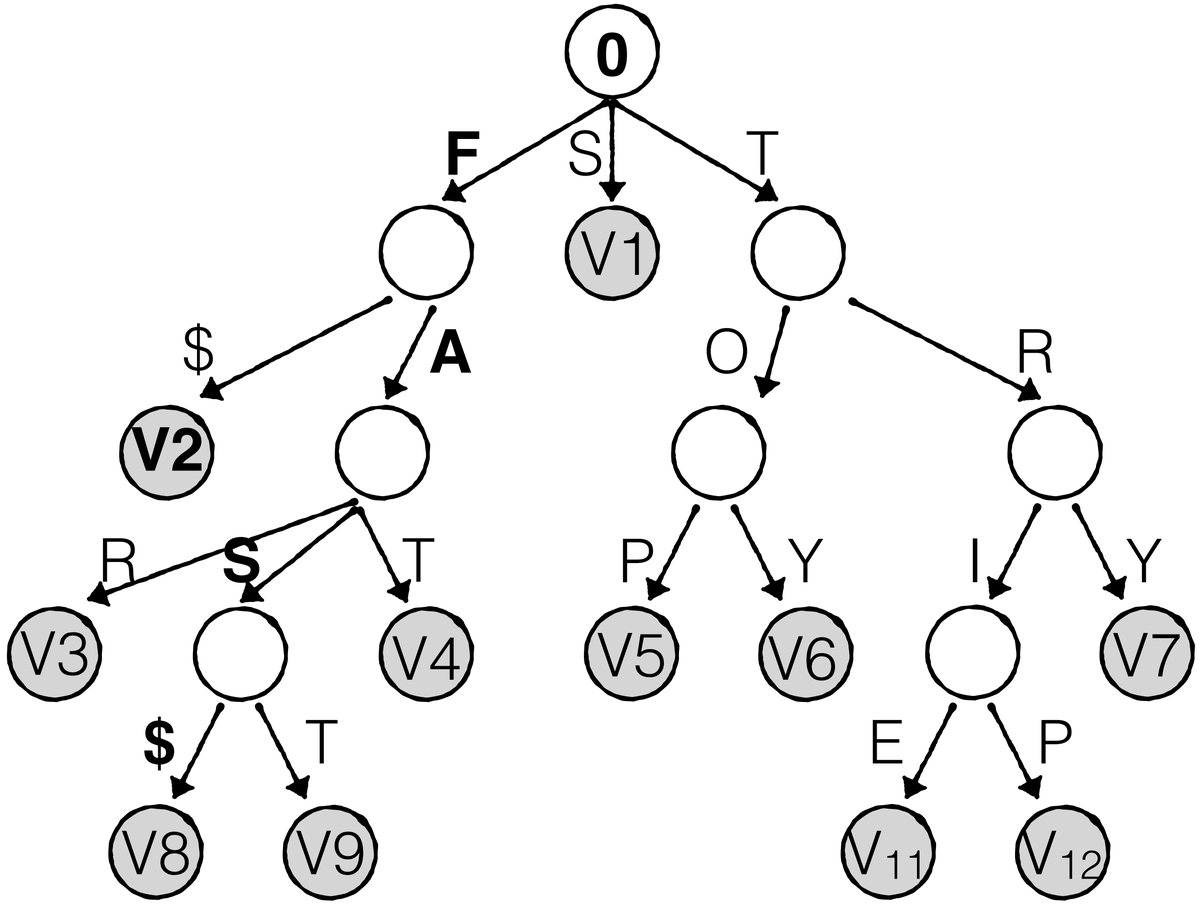


How to encode physically and succinctly?



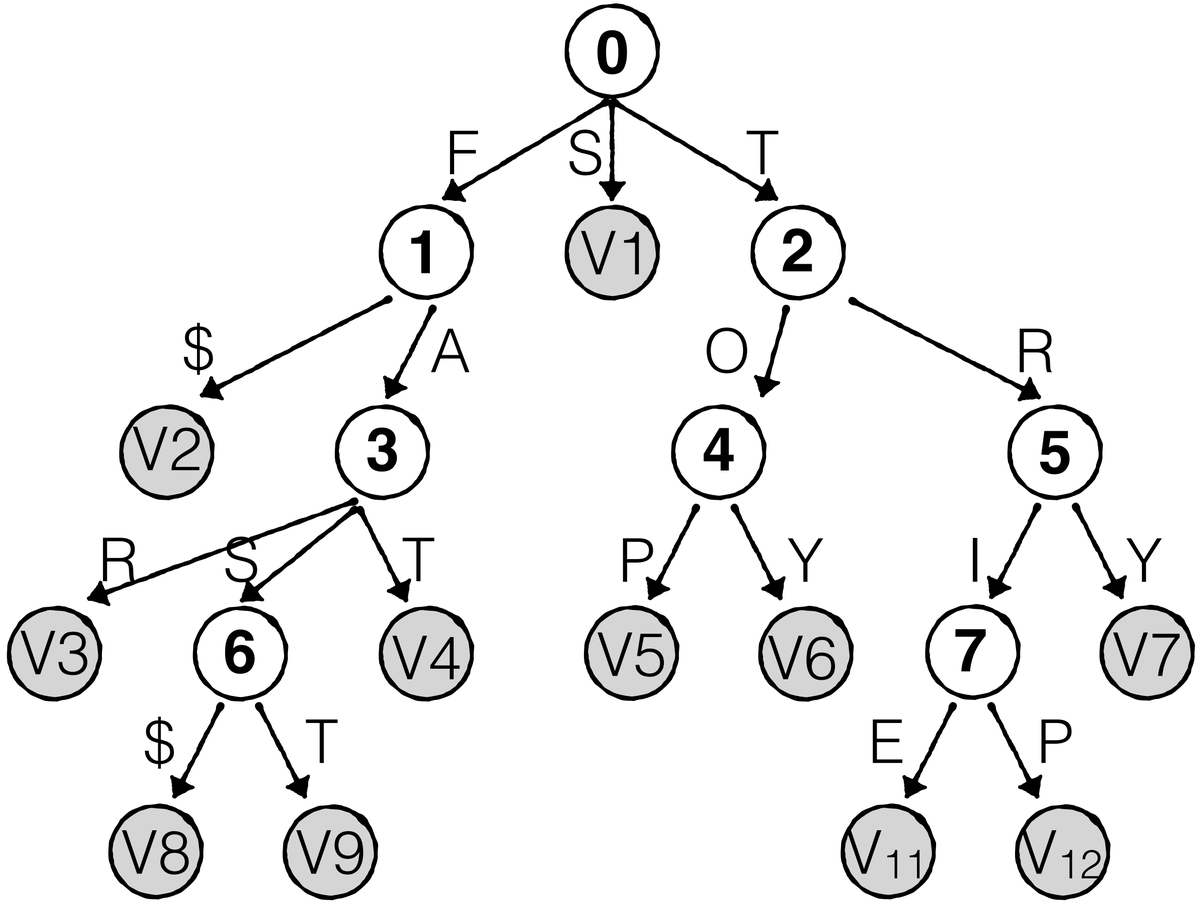
LOUDS: Level-Order Unary Degree Sequence

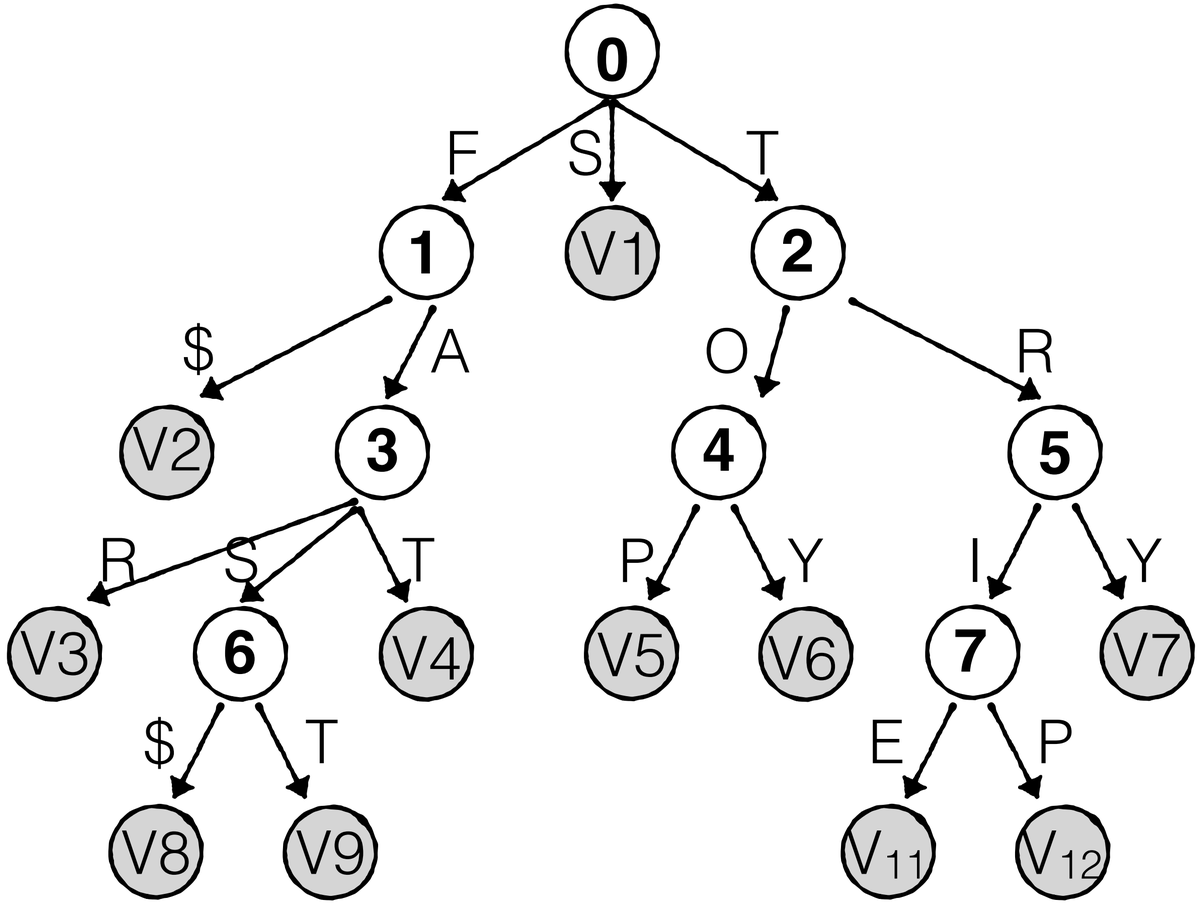
How to encode physically and succinctly?



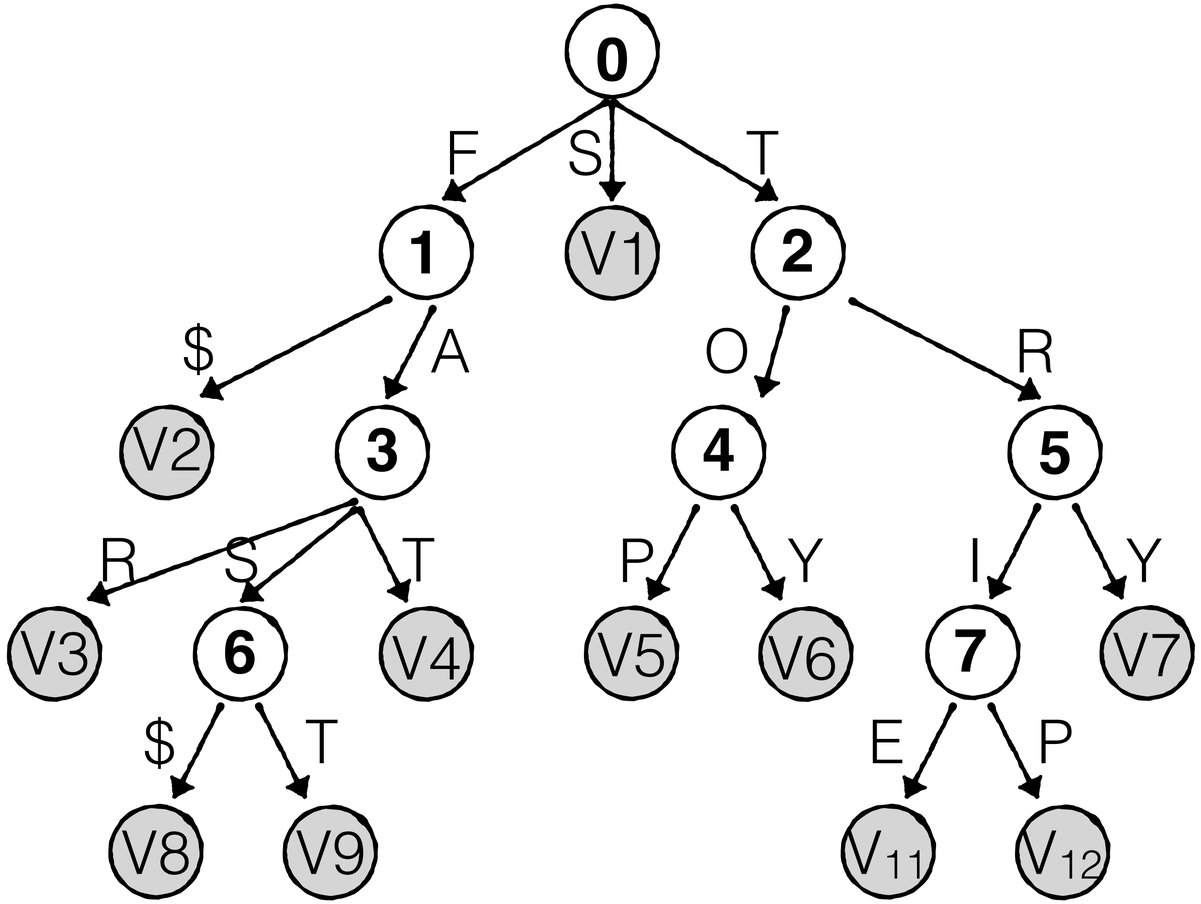
LOUDS: Level-Order Unary Degree Sequence **Variation(!)**

Label internal nodes in breadth-first order for clarity

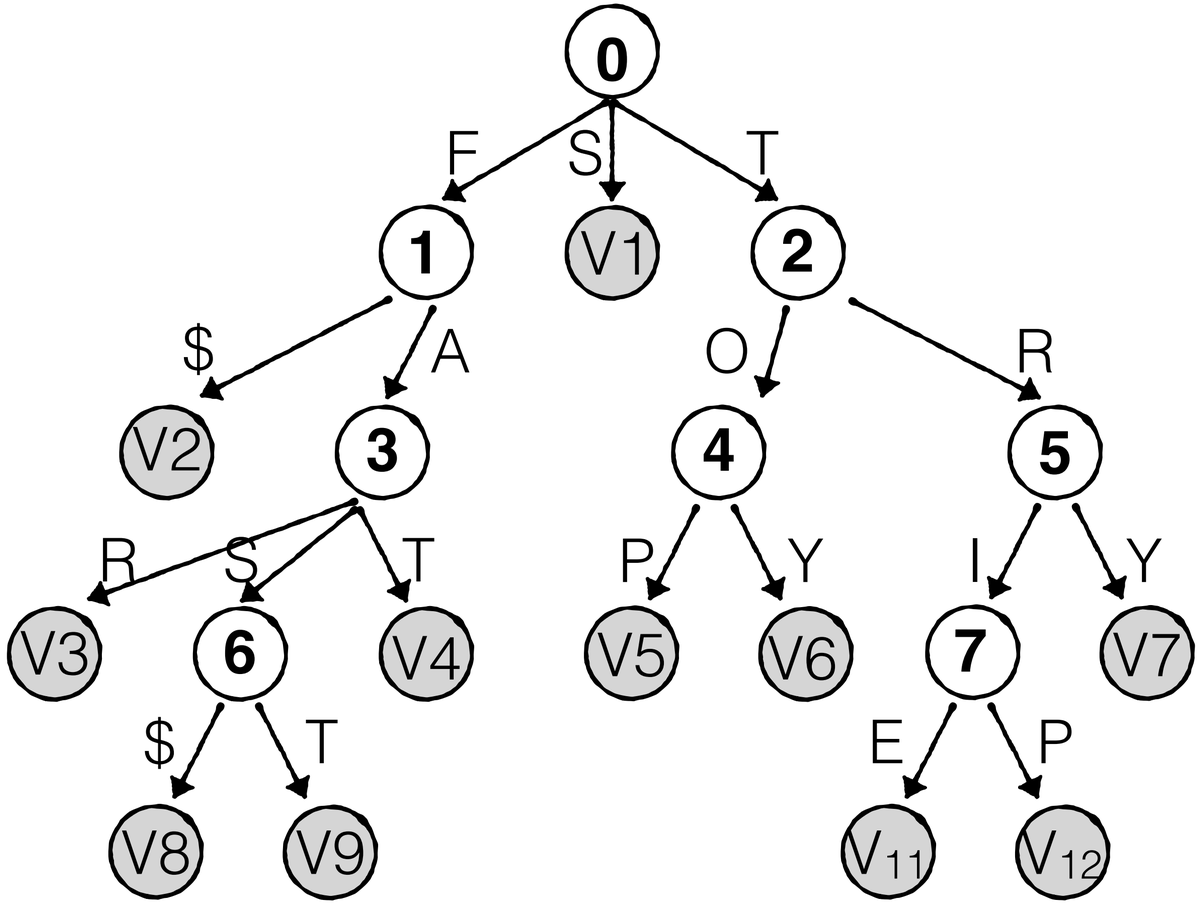




Internal nodes: **0** **1** **2** **3** **4** **5** **6** **7**

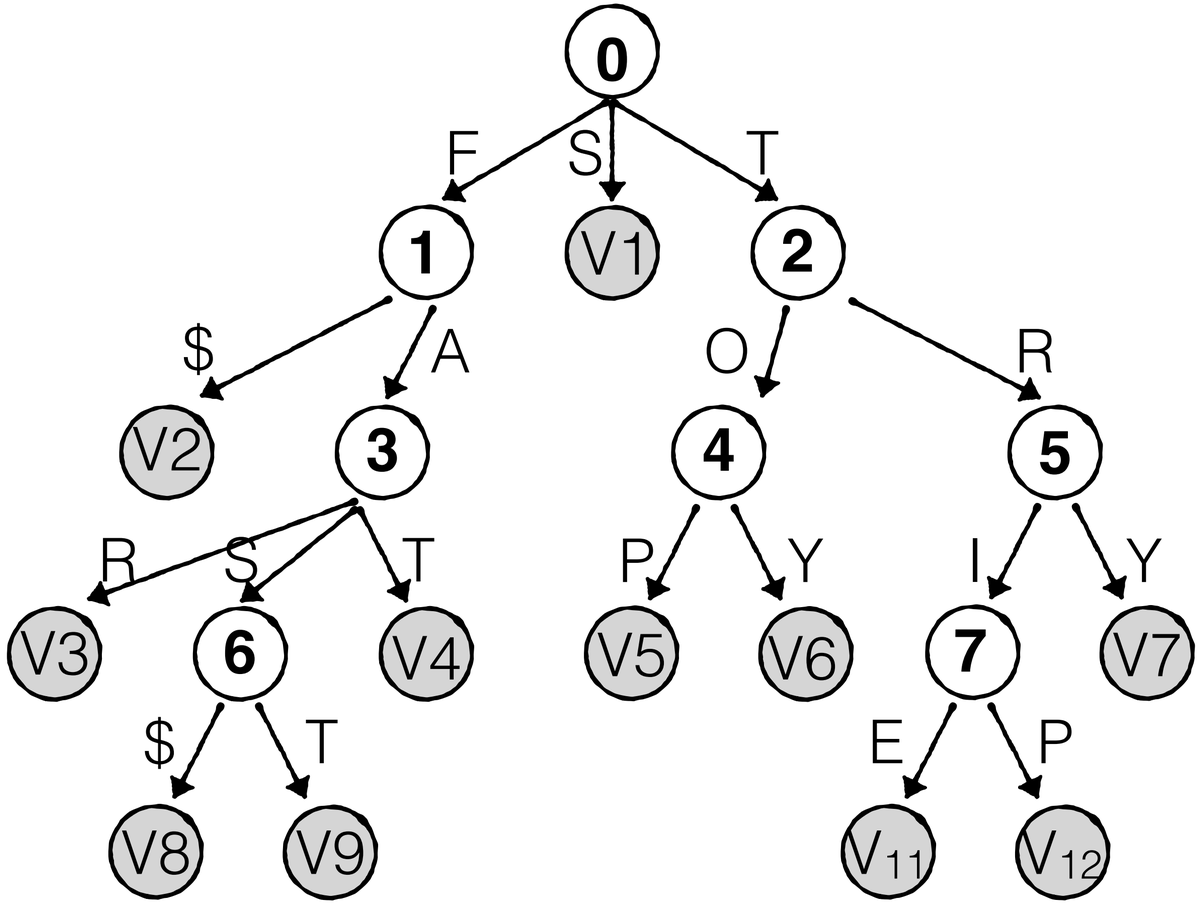


Internal nodes:	0	1	2	3	4	5	6	7
LOUDS:	100	10	100	100	10	10	10	10



Internal nodes:	0	1	2	3	4	5	6	7
LOUDS:	100	10	100	100	10	10	10	10

2 bits per node :)

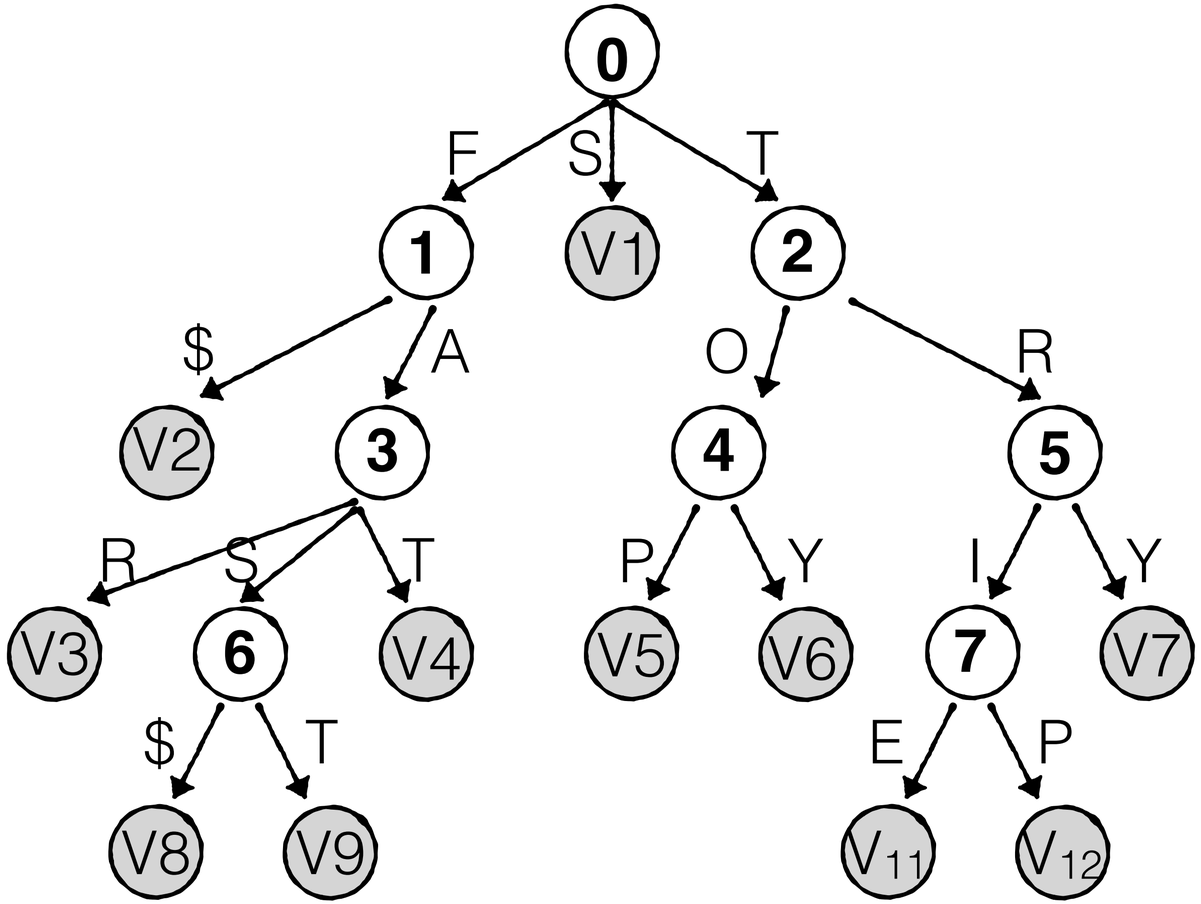


Internal nodes:	0	1	2	3	4	5	6	7
LOUDS:	100	10	100	100	10	10	10	10

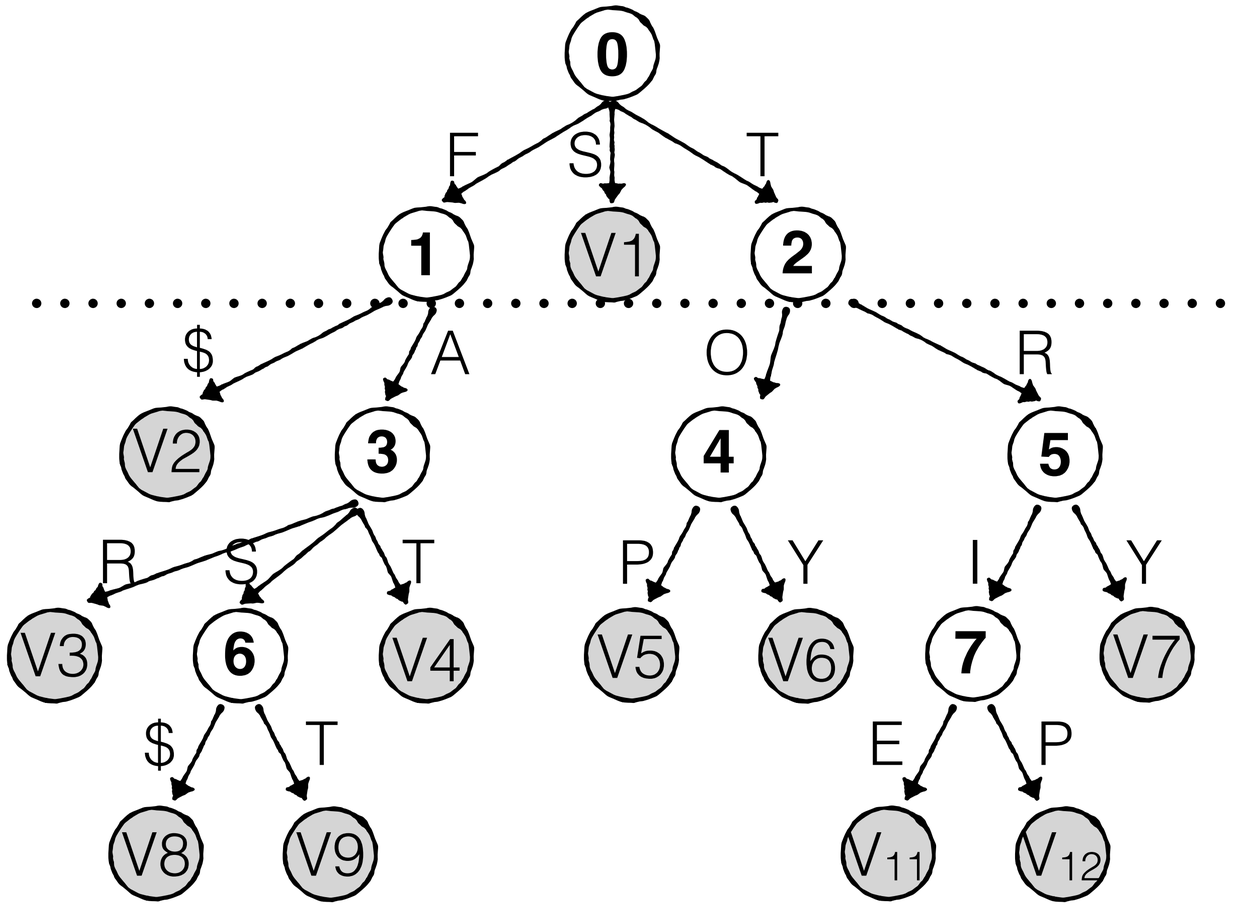
2 bits per node :)

Also fast to traverse using rank/select (shortly)

But we also need to persist characters and values along paths…



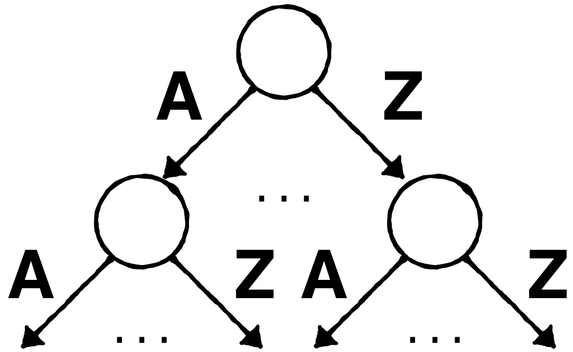
Internal nodes:	0	1	2	3	4	5	6	7
LOUDS:	100	10	100	100	10	10	10	10



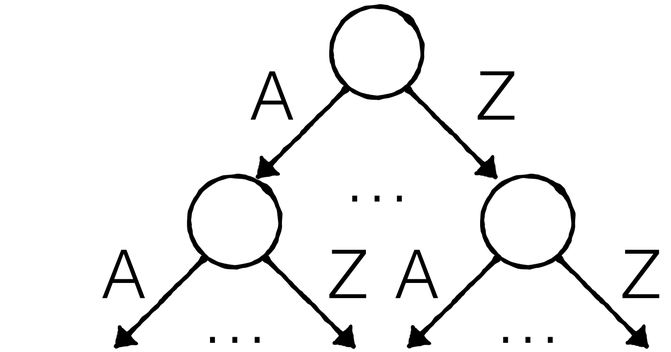
Dense encoding

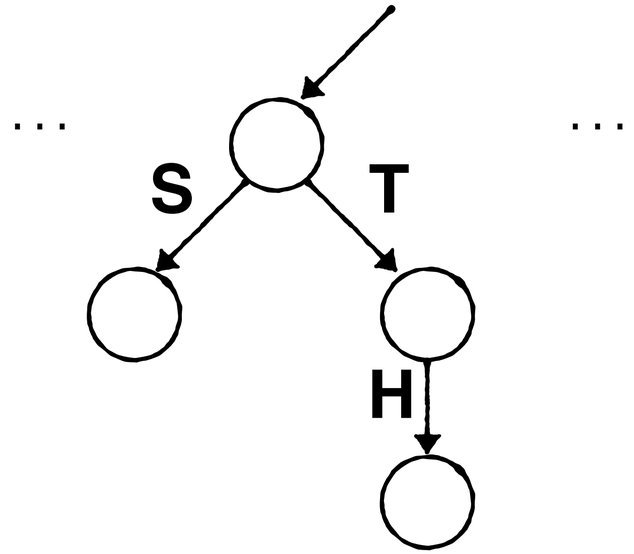
Sparse encoding

Typically, the upper levels of the trie are more full

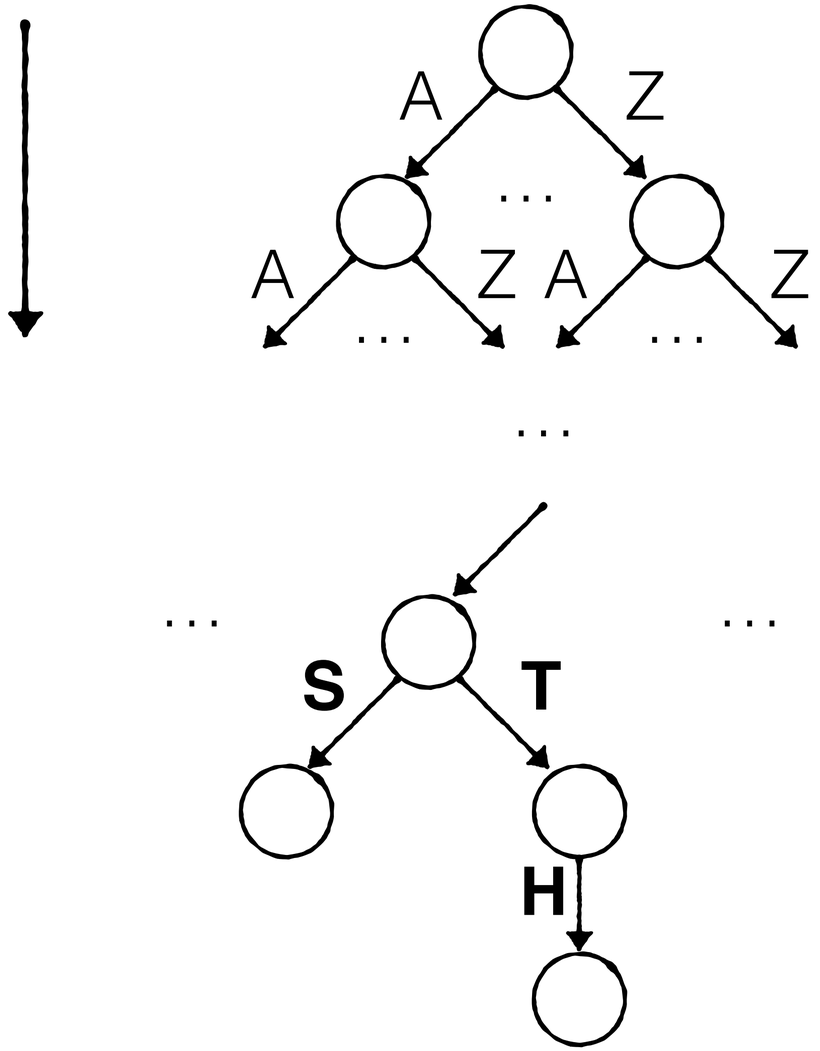


Typically, the upper levels of the trie are more full

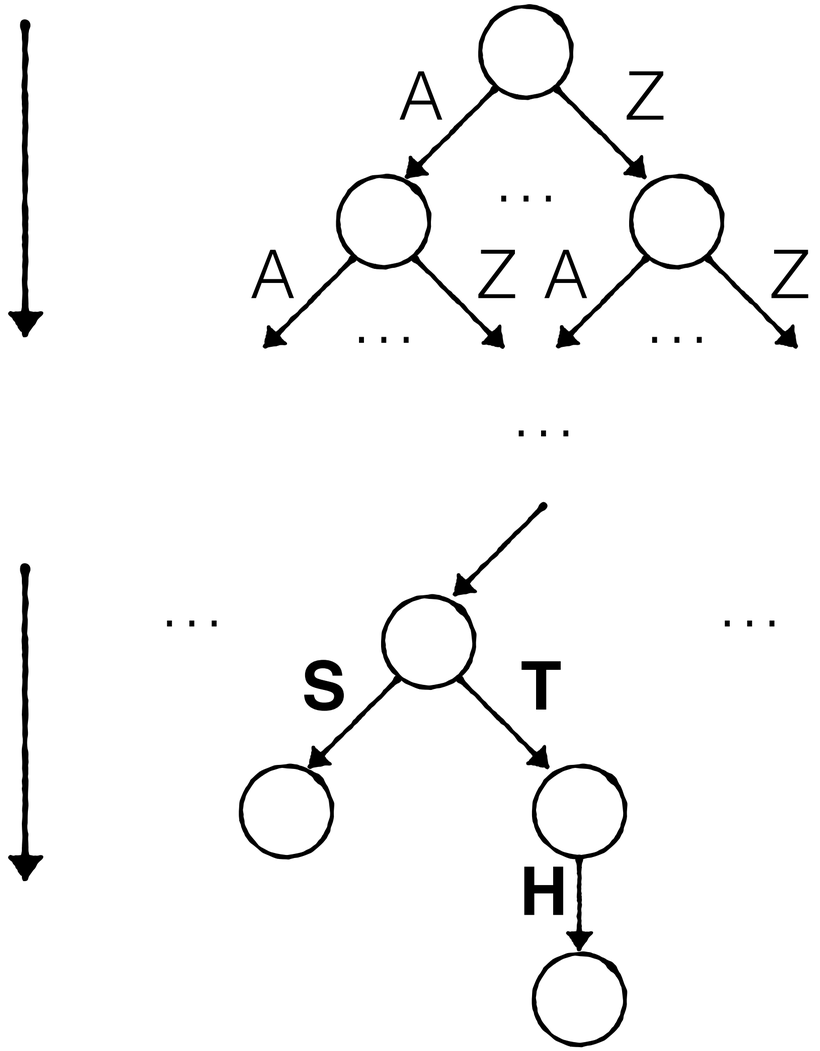




More queries go through base layers

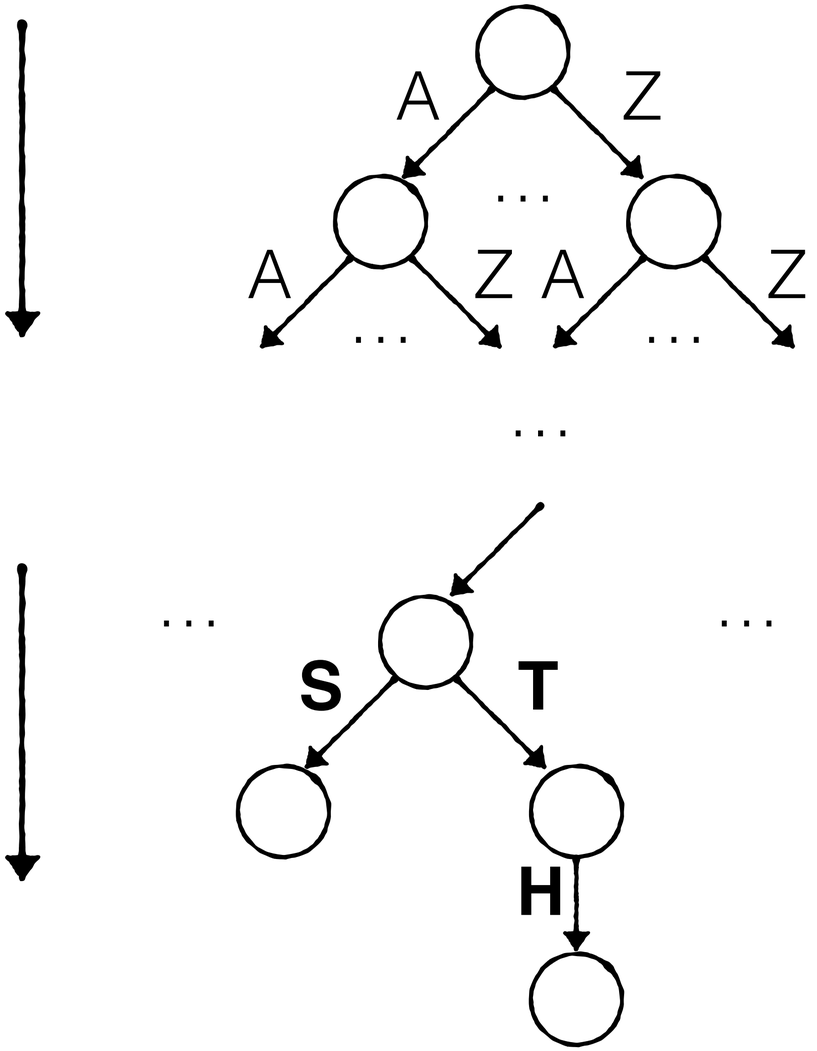


More queries go through base layers



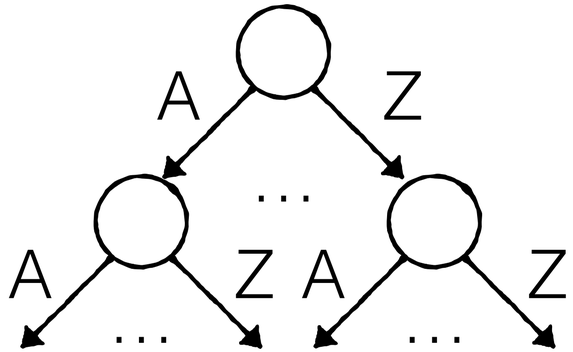
A leaf is reached on avg. by fewer queries

More queries go through base layers

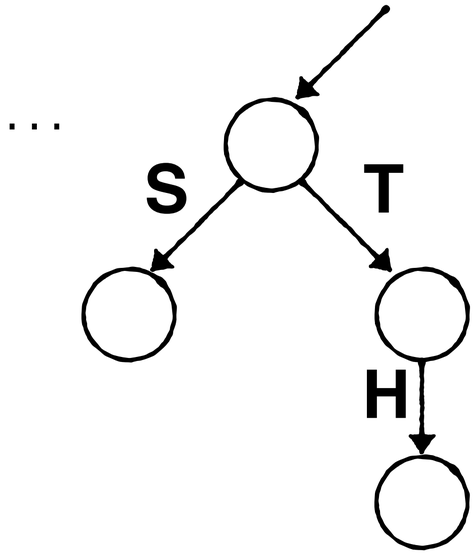


A leaf is reached on avg. by fewer queries

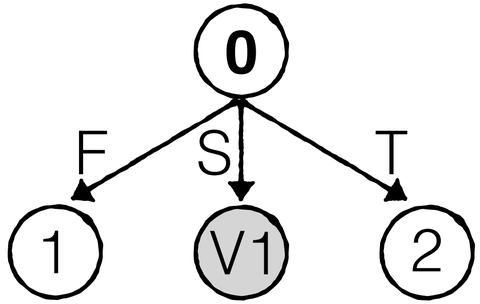
Exponentially more nodes as we move down



Optimize for speed



Optimize for space

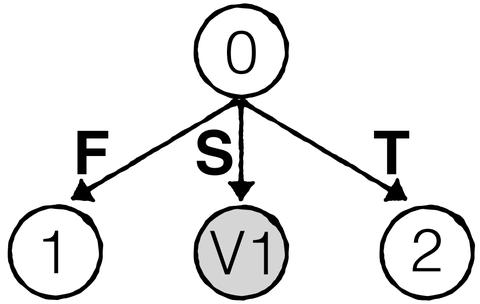


Edges

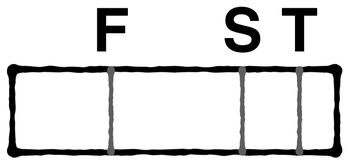
Node 0

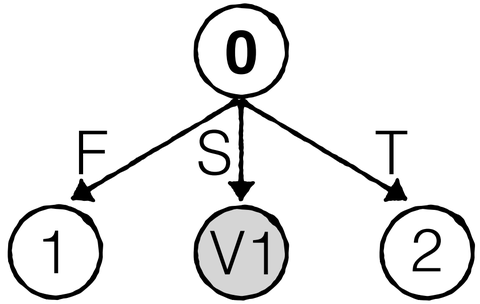
256 bits

One bit set for every connected character



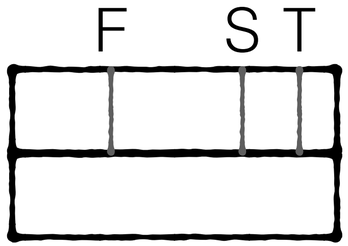
Edges

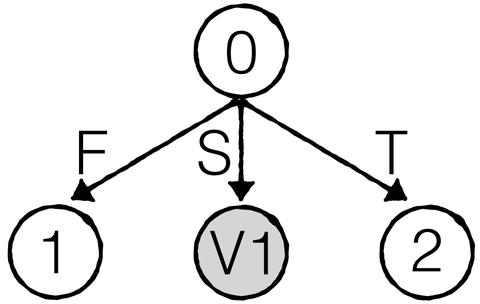




Edges

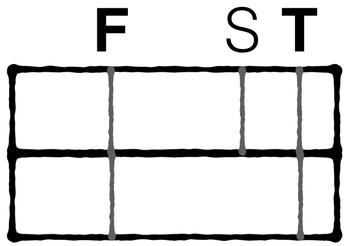
Has-child

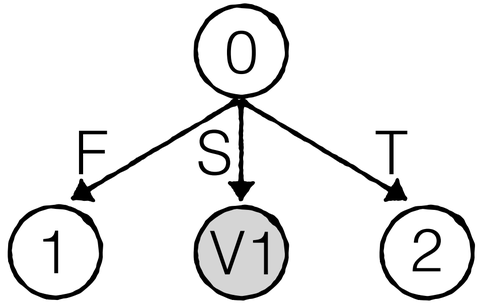


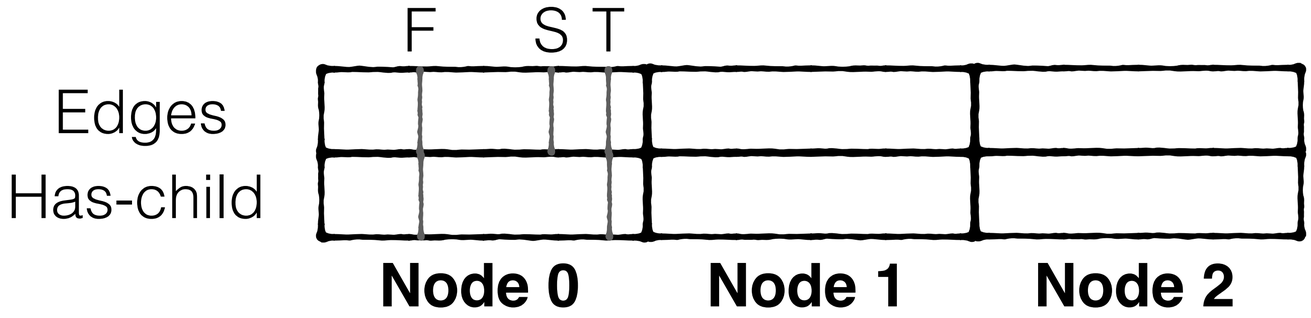


Edges

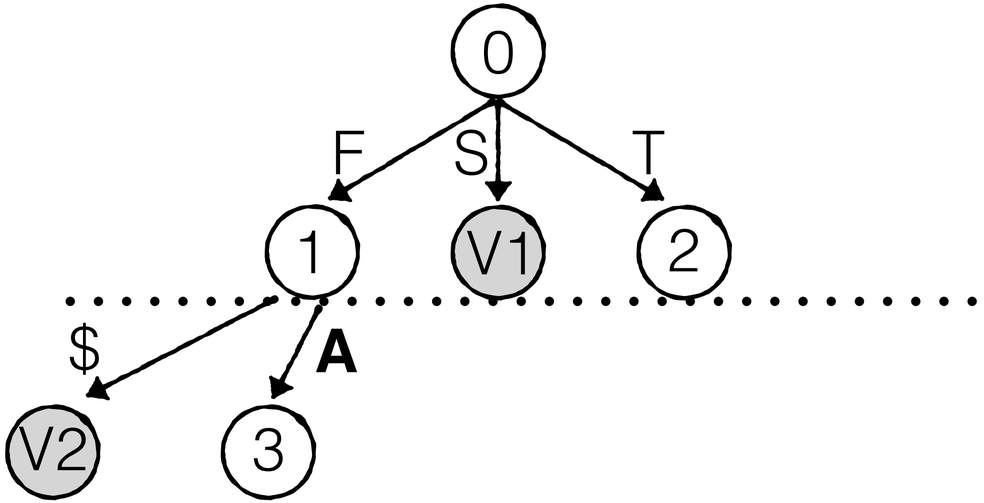
Has-child



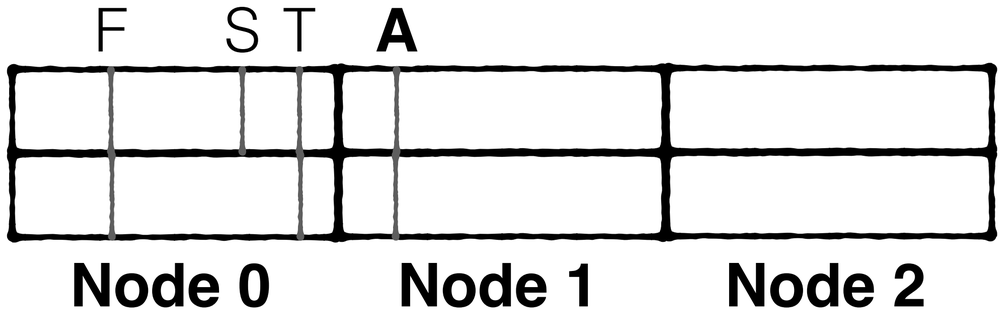




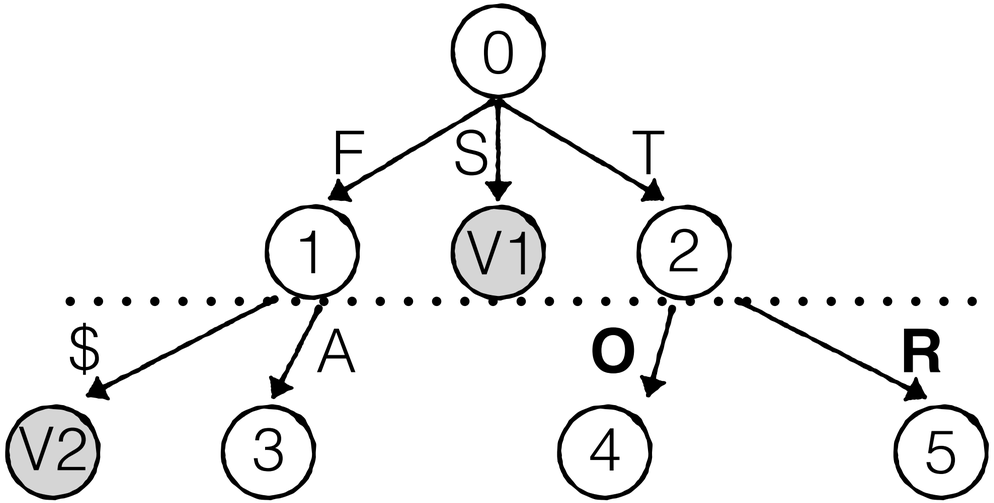
Continue in breadth-first order for each internal node



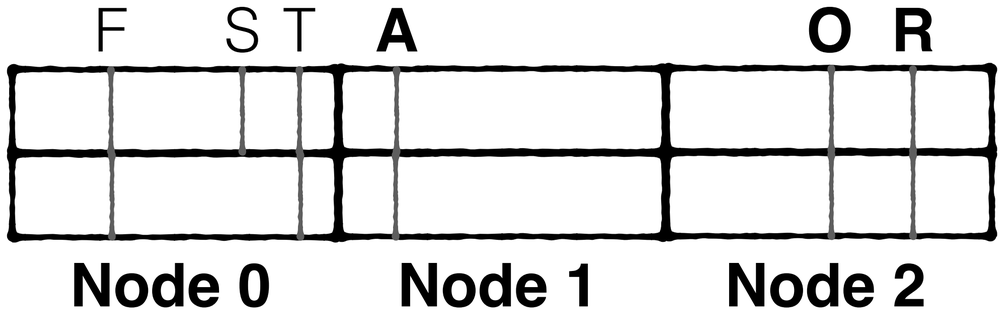
Edges
Has-child



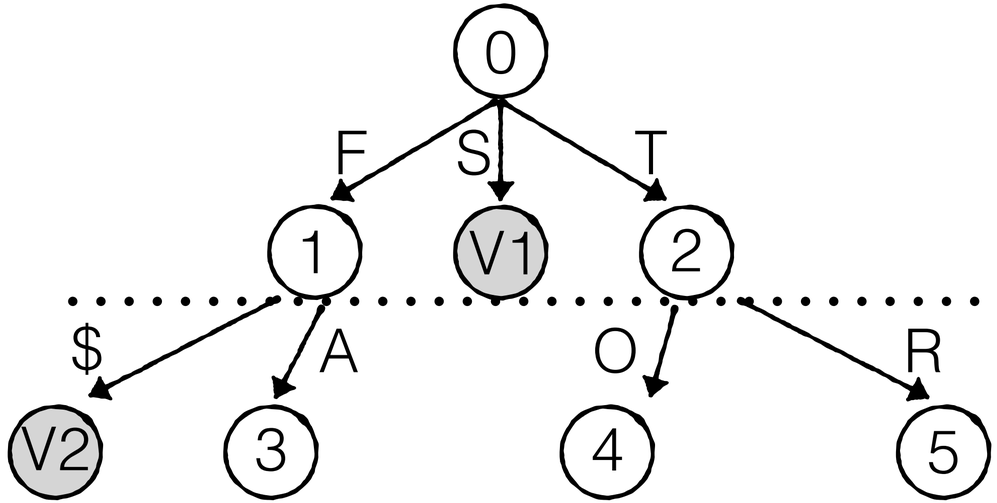
Continue in breadth-first order
for each internal node

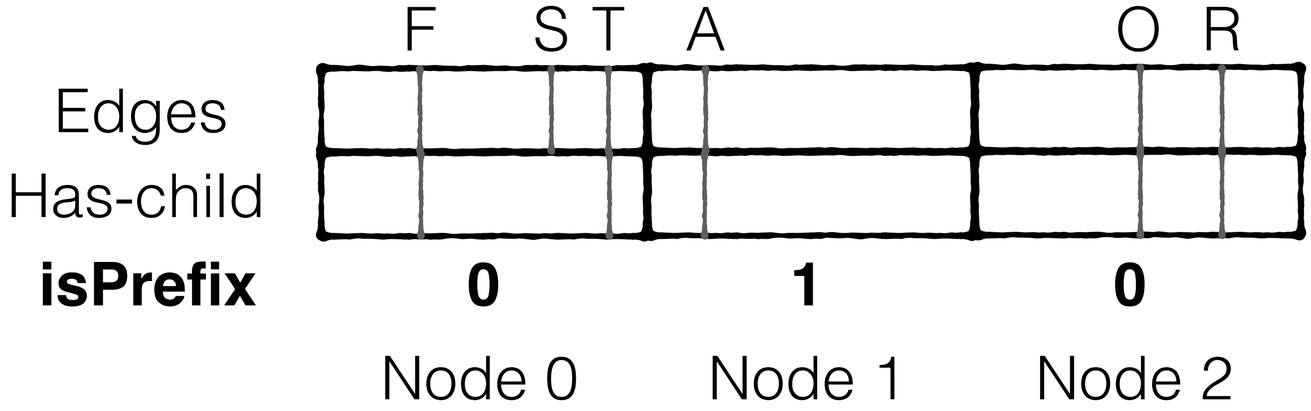


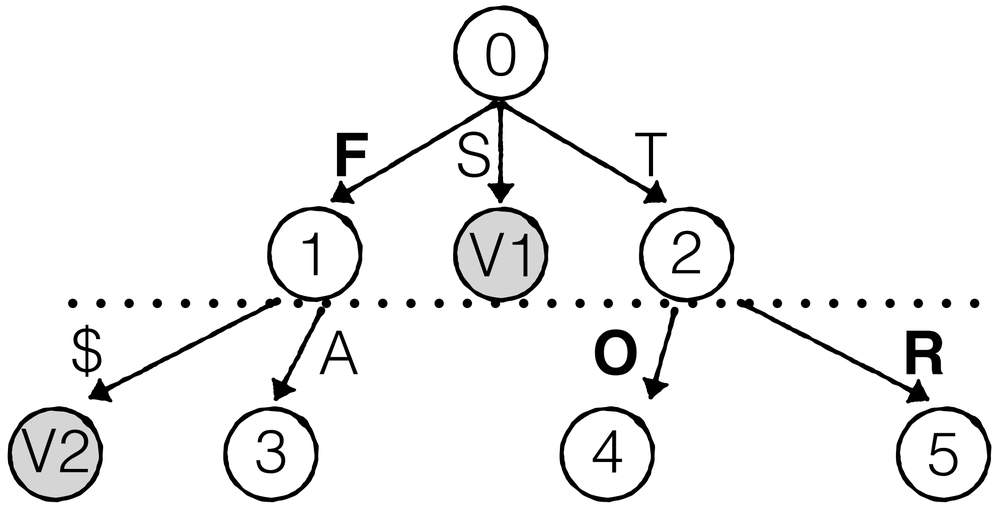
Edges
Has-child

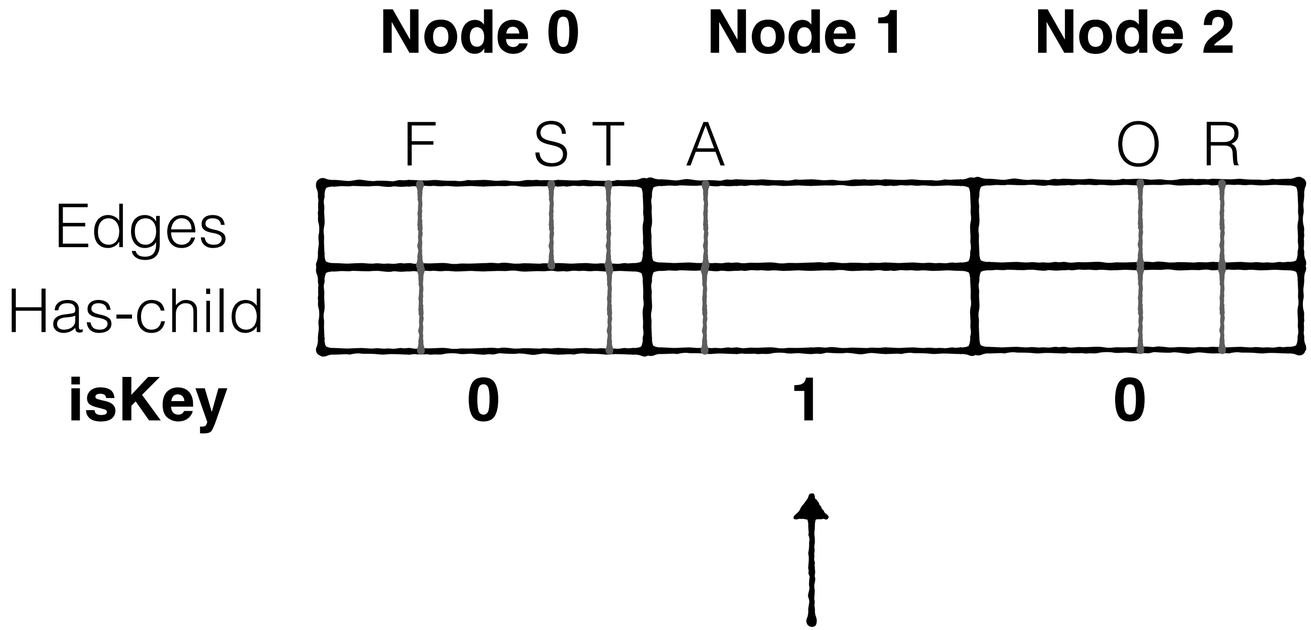


Continue in breadth-first order
for each internal node

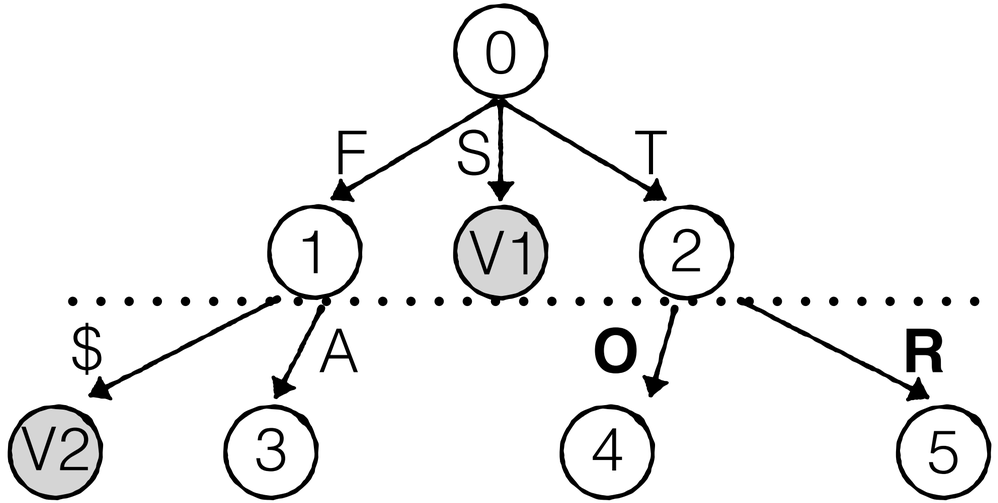

0
F
S
T
1
V1
2
$
A
O
R
V2
3
4
5

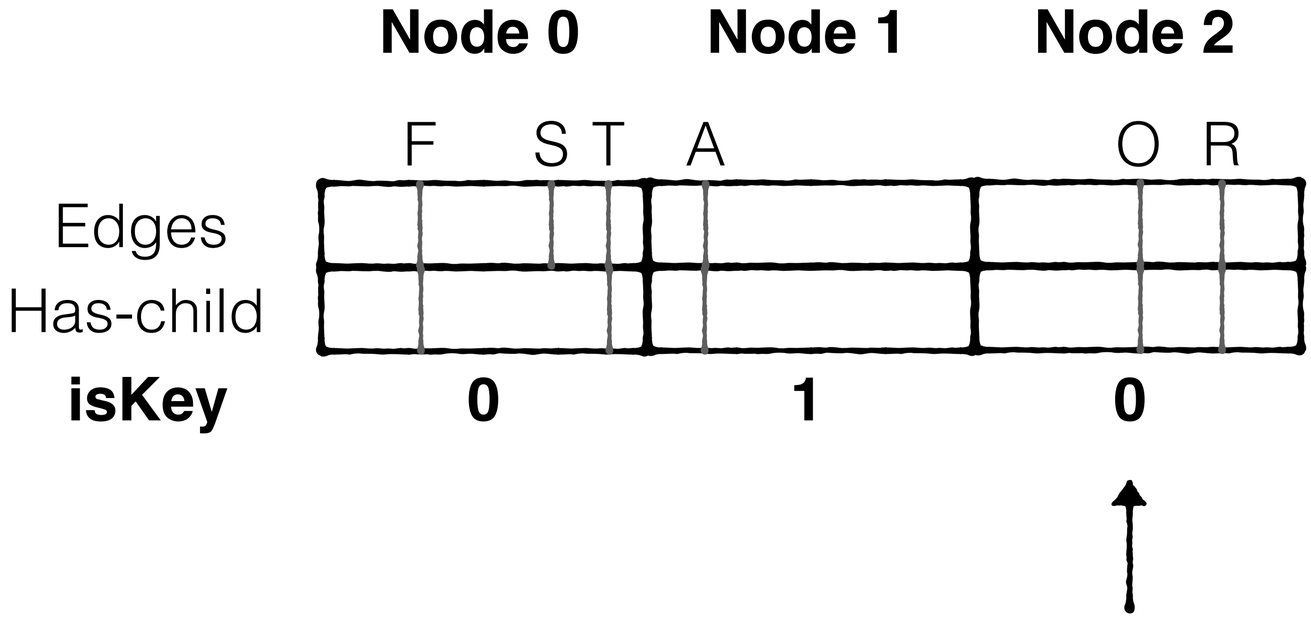

F
S
T
A
O
R
Edges
Has-child
isPrefix
0
1
0
Node 0
Node 1
Node 2


0
F
S
T
1
V1
2
$
A
O
R
V2
3
4
5

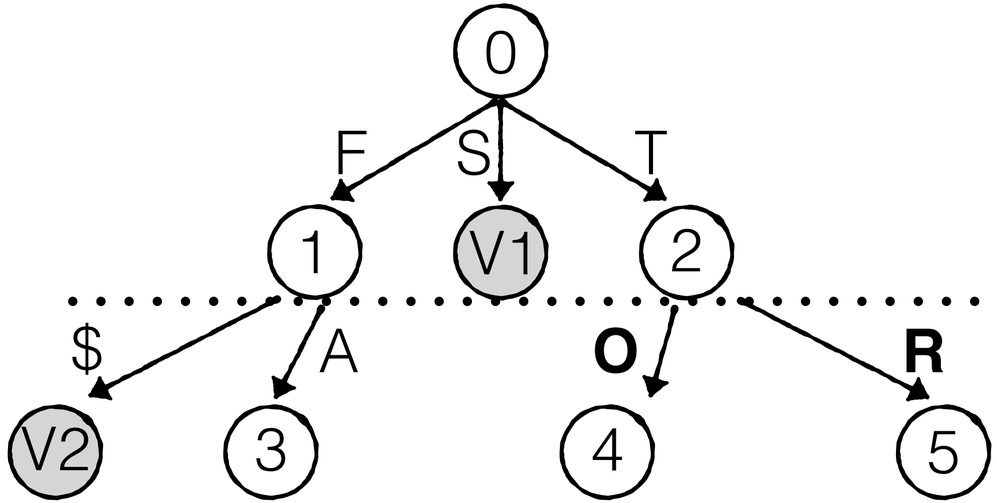

Node 0
Node 1
Node 2
F
S
T
A
O
R
Edges
Has-child
isKey
0
1
0

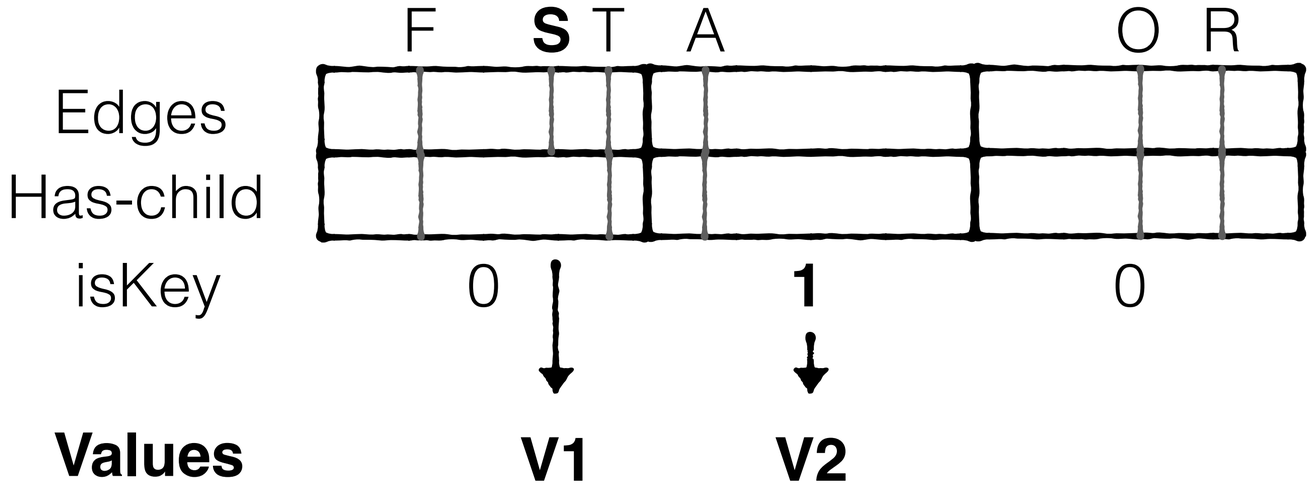
“F” is full key

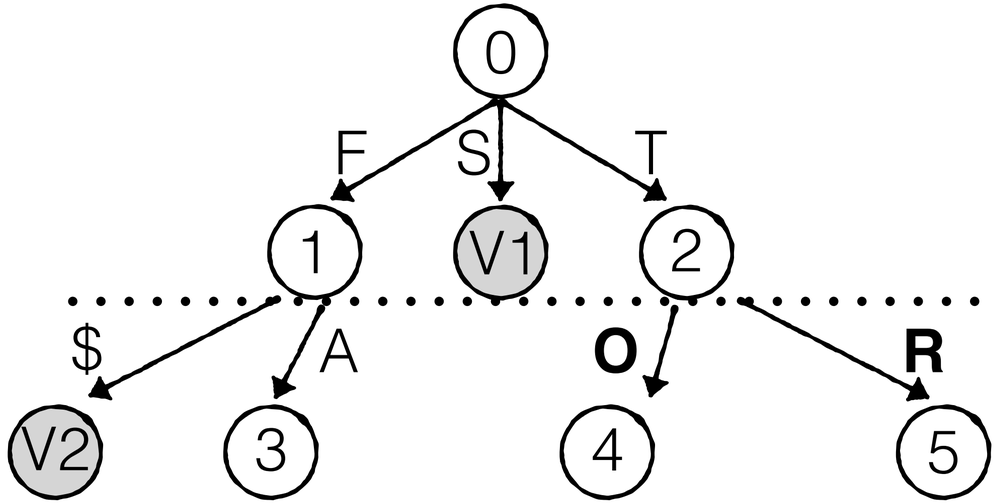


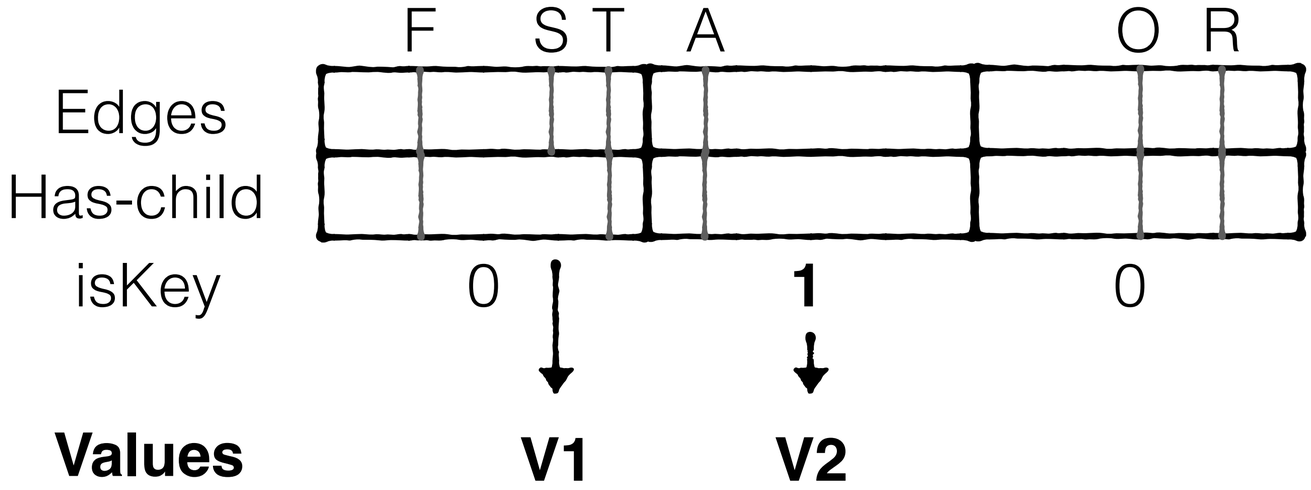


“T” is not full key


0
F
S
T
1
V1
2
$
A
O
R
V2
3
4
5

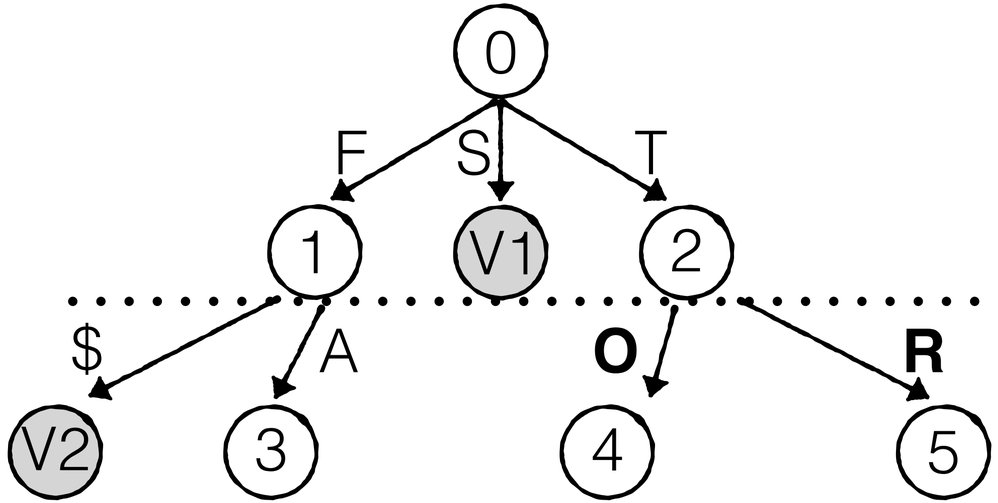

F
S
T
A
O
R
Edges
Has-child
isKey
0
1
0
Values
V1
V2

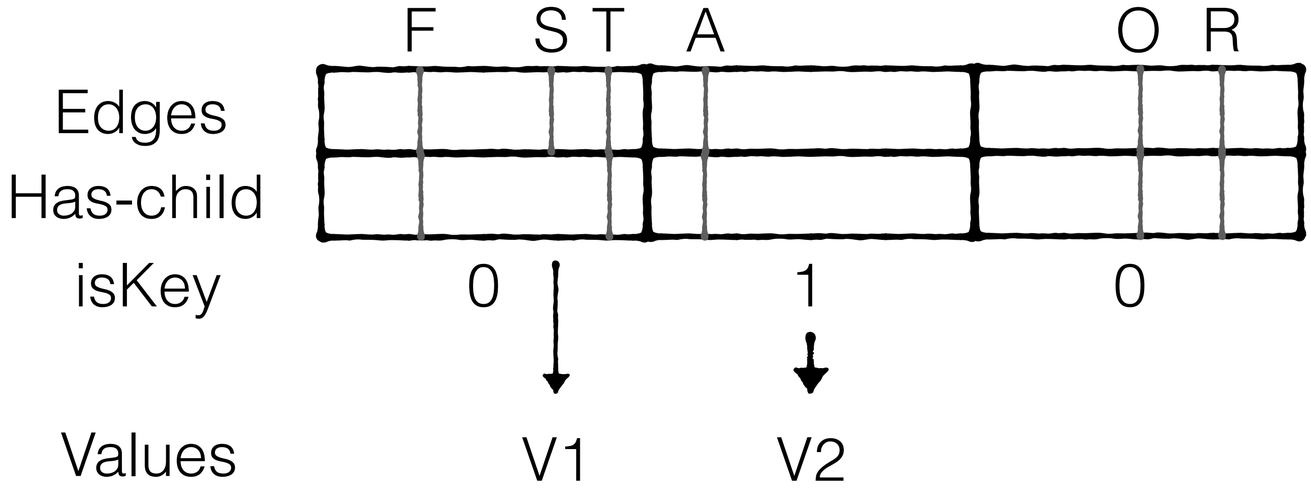


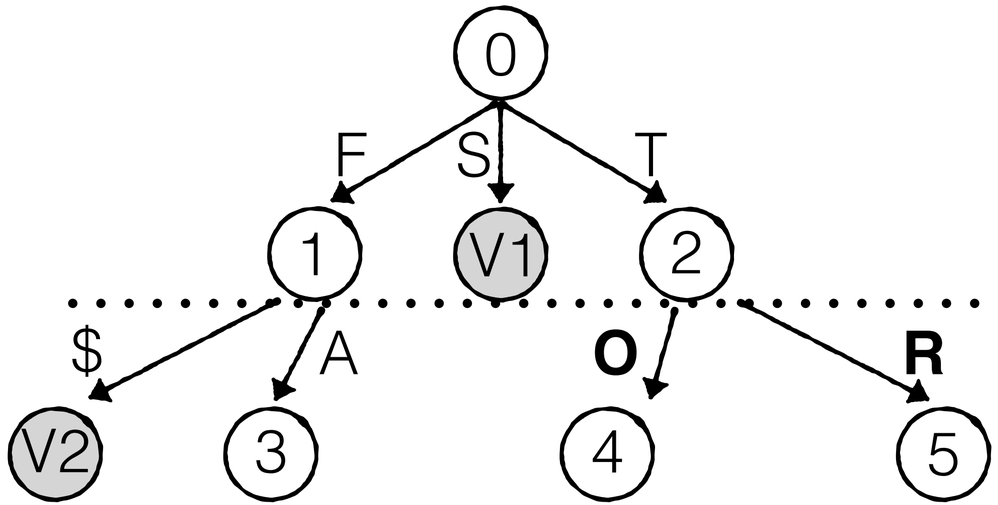


Stored contiguously in an array

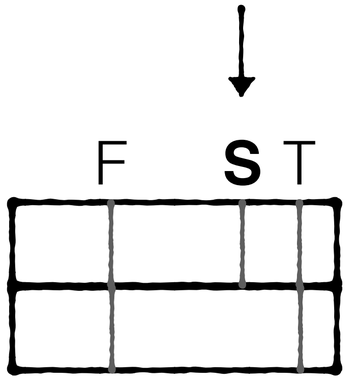
Does “S” exist?


0
F
S
T
1
V1
2
$
A
O
R
V2
3
4
5


F
S
T
A
O
R
Edges
Has-child
isKey
0
1
0
Values
V1
V2



Does “S” exist?



Edges

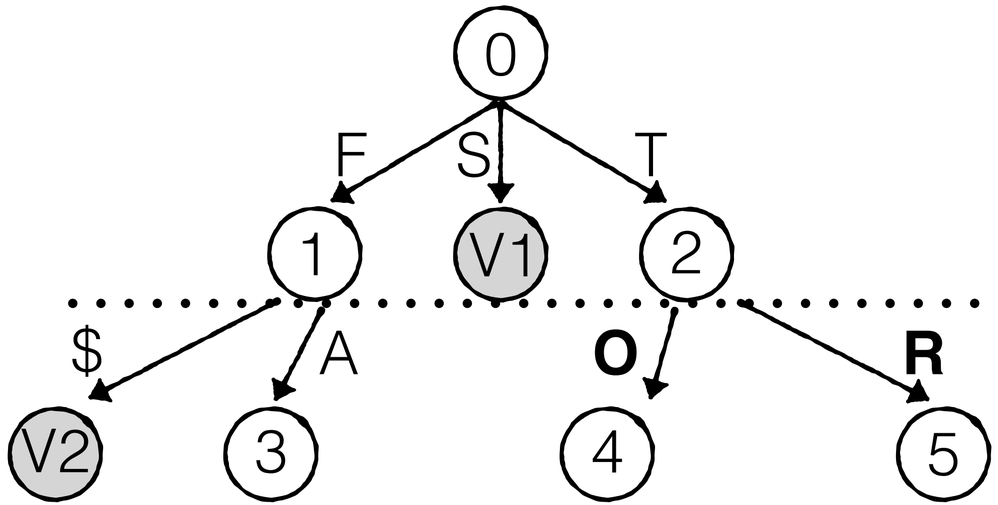
Has-child

isKey

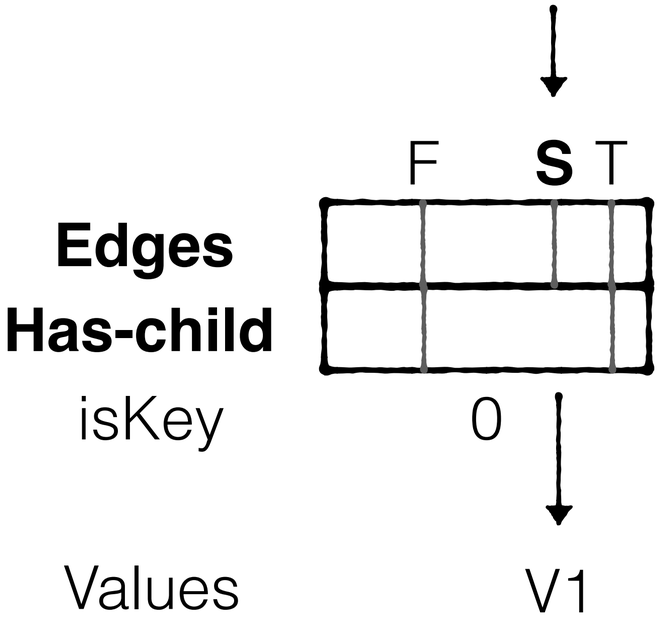
0

Values

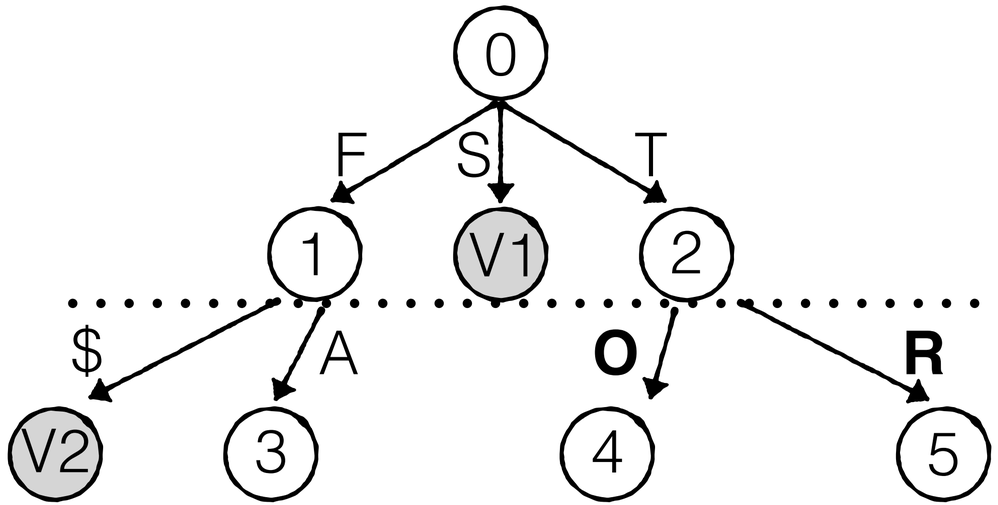
V1

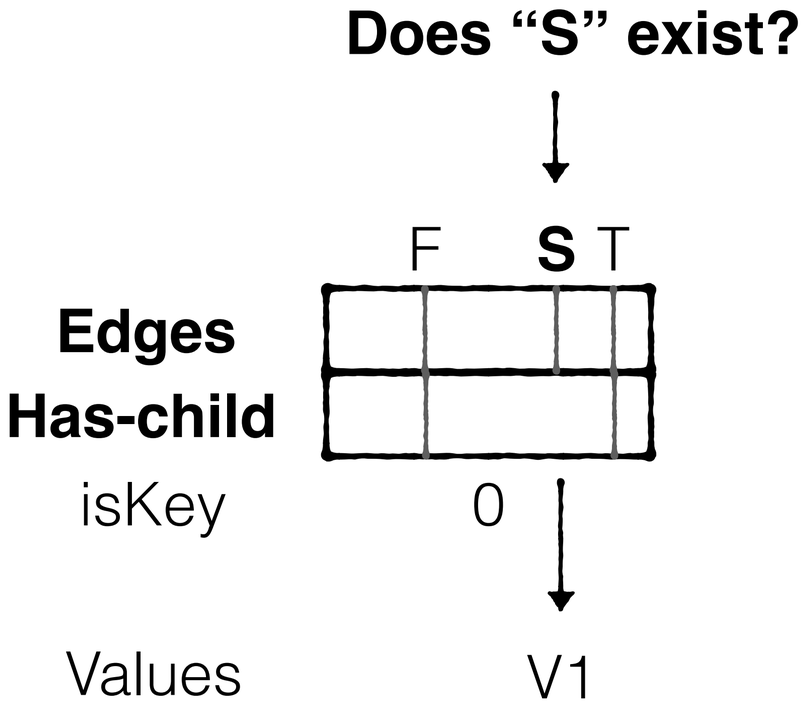


Does “S” exist?



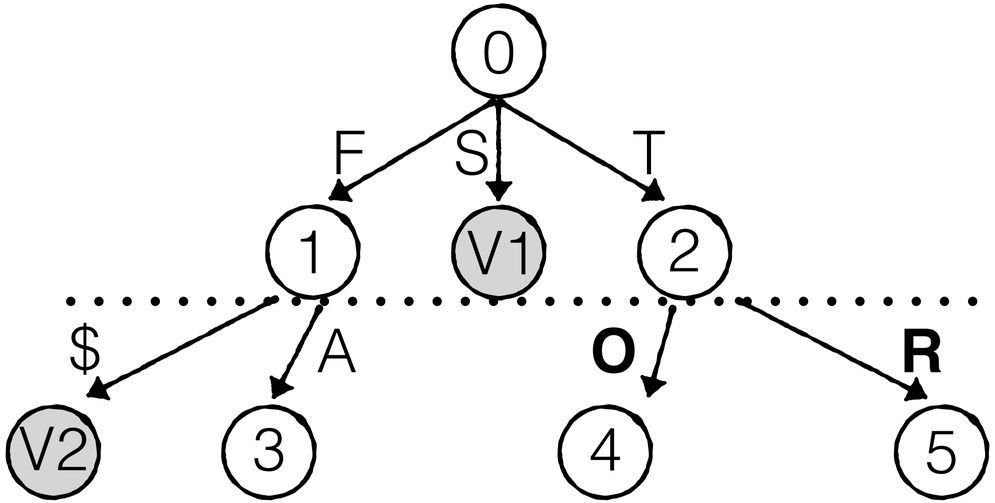
We observe that S exists and has no children, meaning it must be a full key

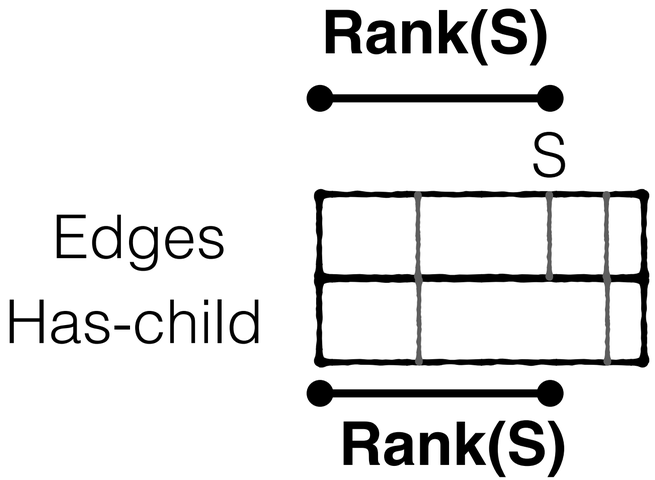


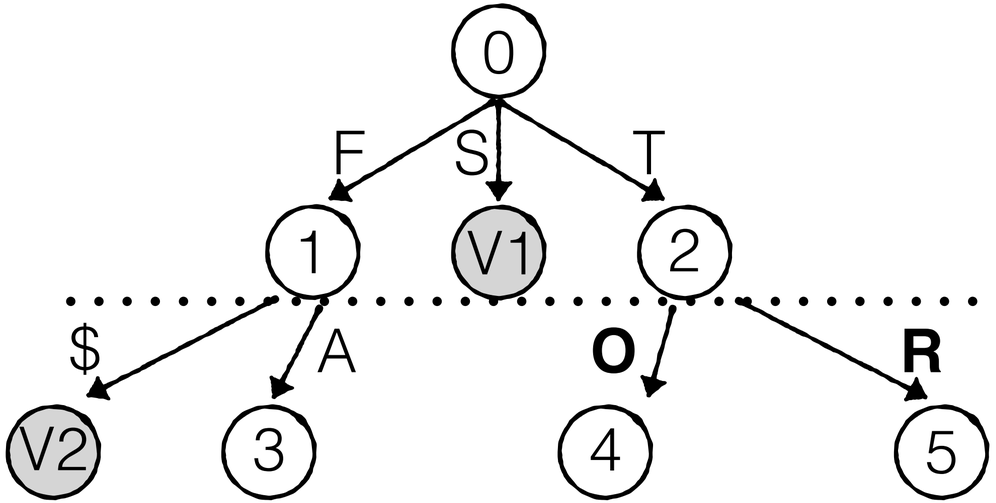


We observe that S exists and has no children, meaning it must be a full key

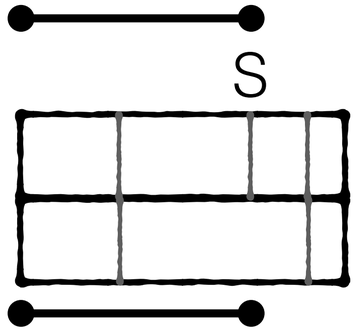
How to locate its value?


0
F
S
T
1
V1
2
$
A
O
R
V2
3
4
5


Rank(S)
S
Edges
Has-child
Rank(S)

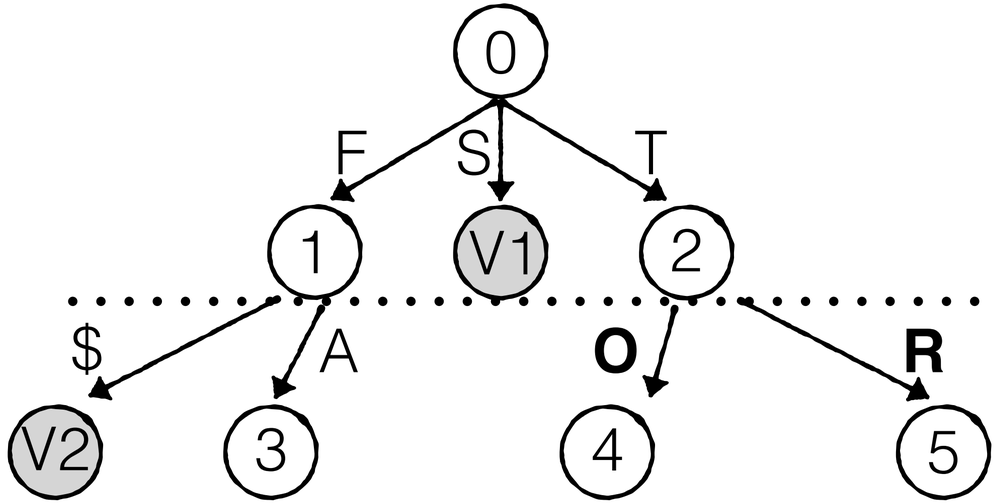


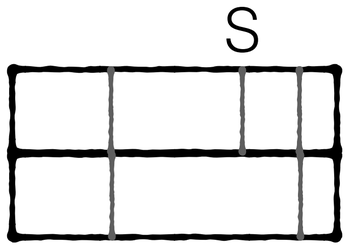
Rank(Edges, S) = **1**

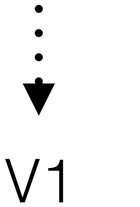


Rank(Has-child, S) = **1**

S value offset = **Rank**(Edges, S) - **Rank**(Has-child, S) = **0**

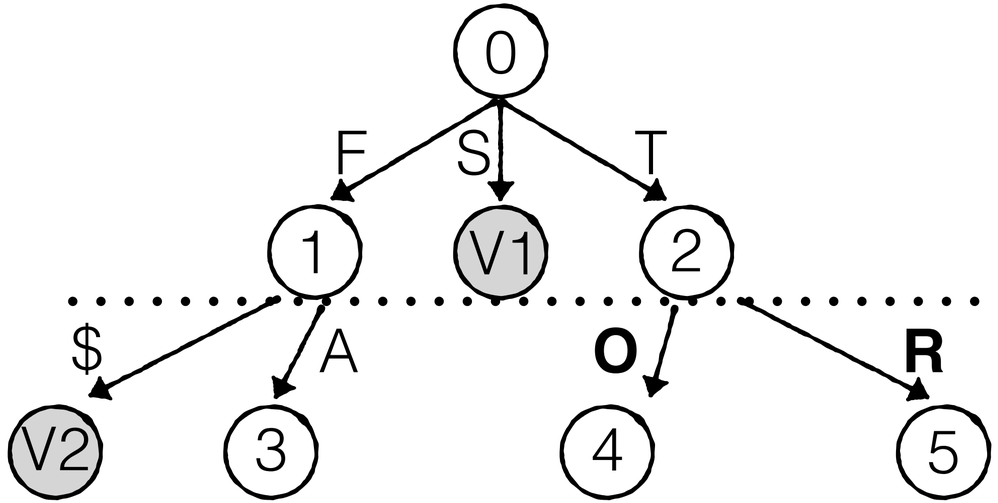


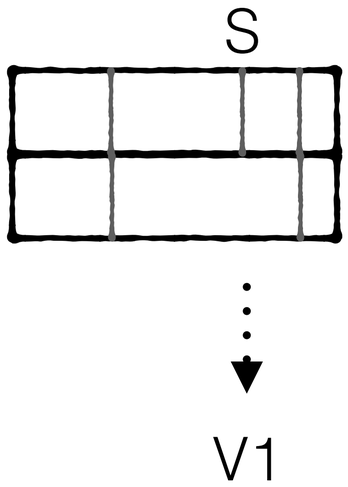




V1

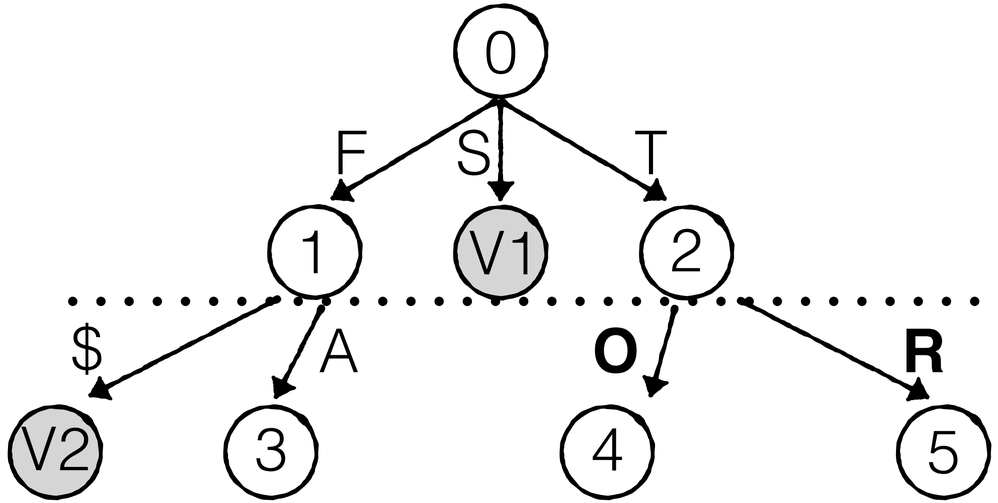
S value offset = Rank(Edges, S) - Rank(Has-child, S) = 0

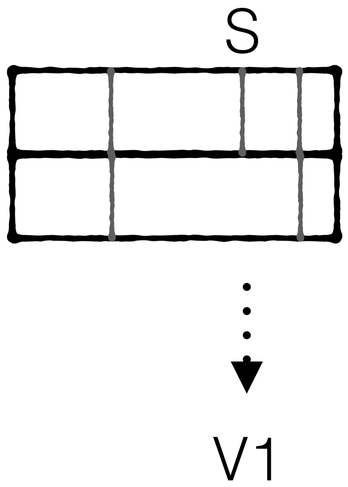




Constant time per each node access :)

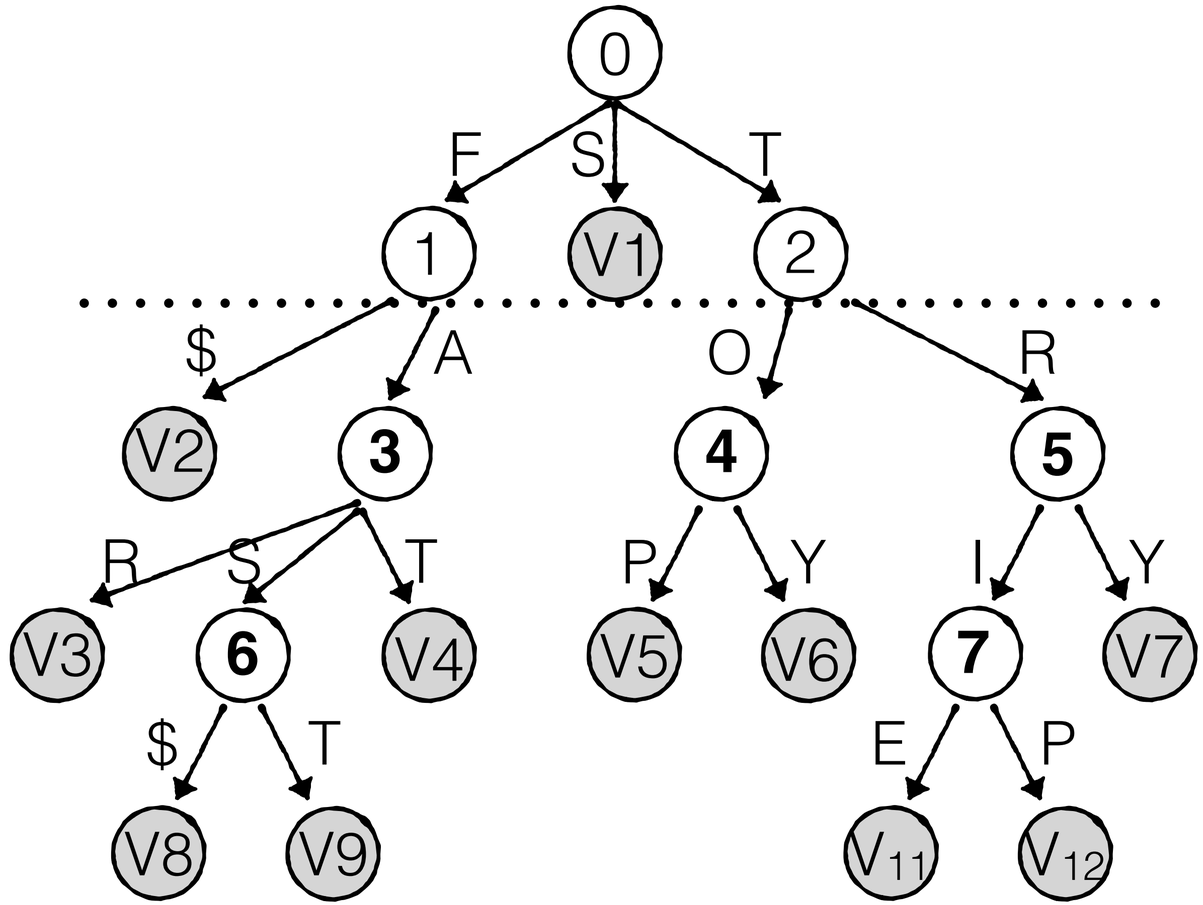
S value offset = Rank(Edges, S) - Rank(Has-child, S) = 0





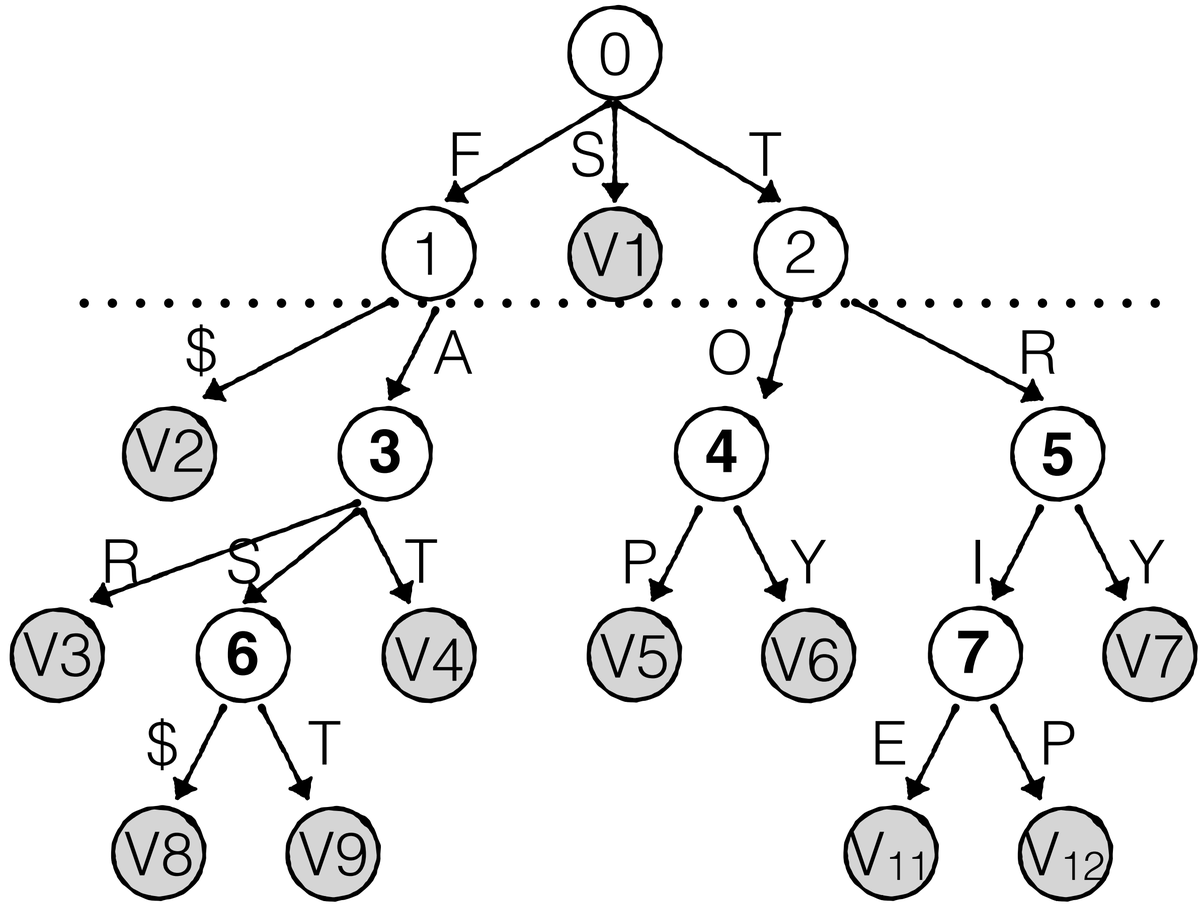
Constant time per each node access :)

Few bits per entry when base nodes have many edges

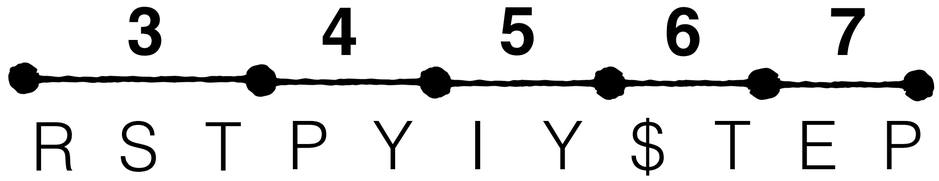


Internal Nodes in breadth first order

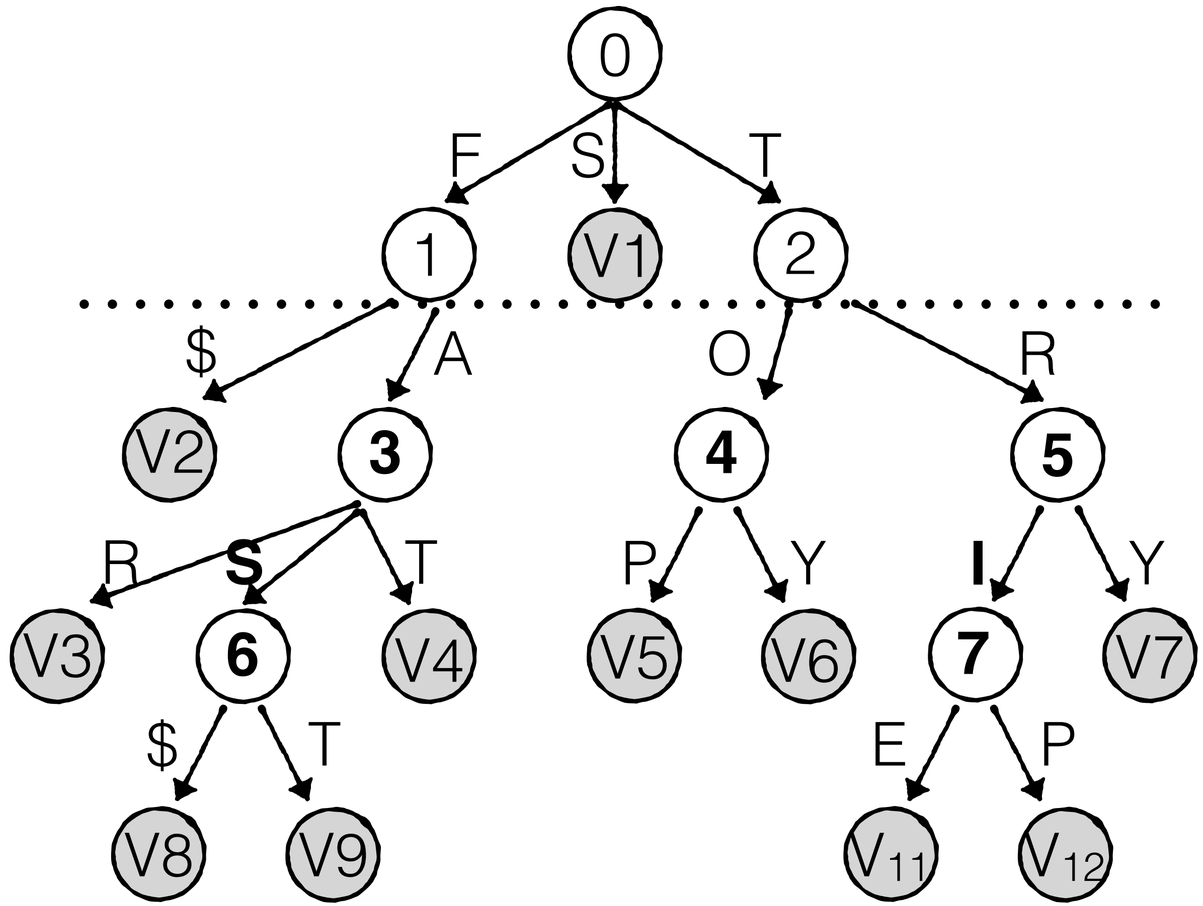
3 4 5 6 7



Internal Nodes in breadth first order

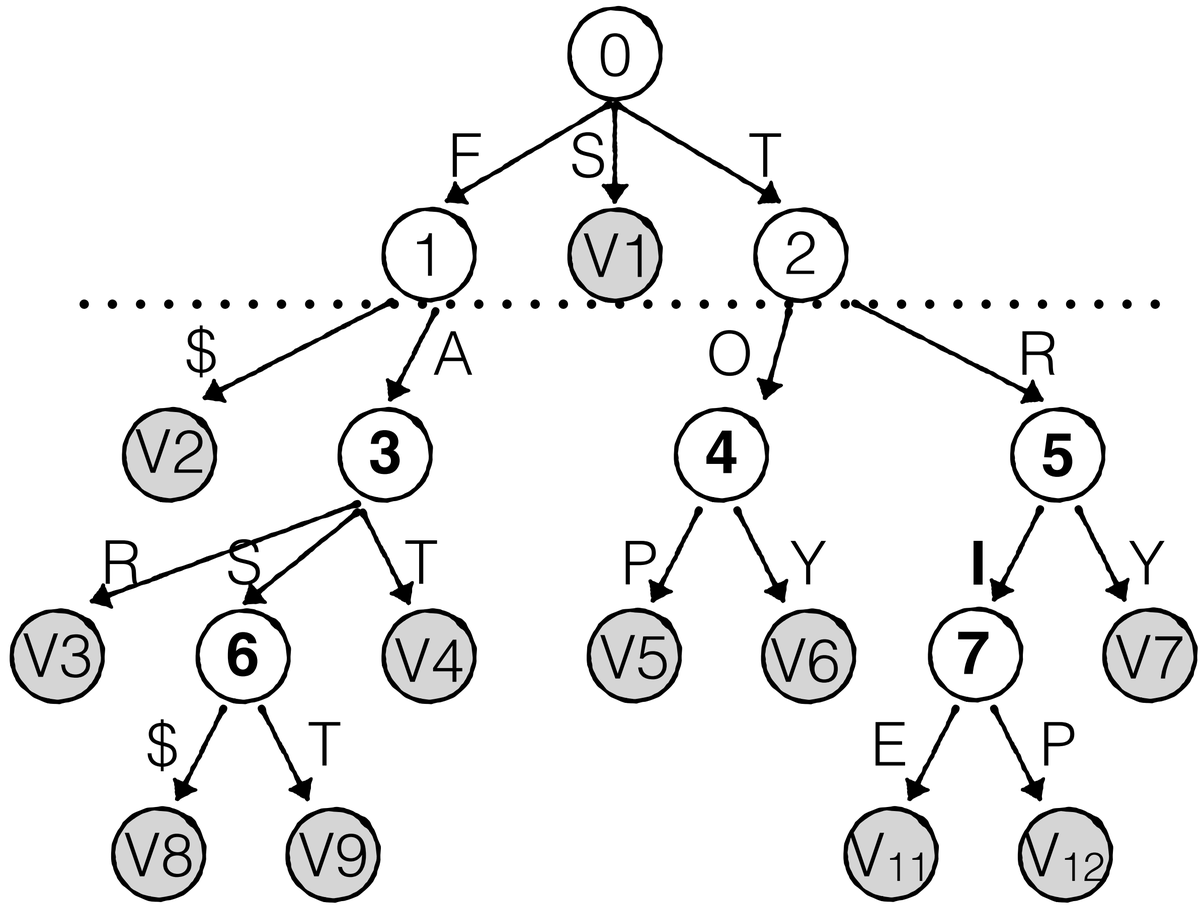


Store children contiguously

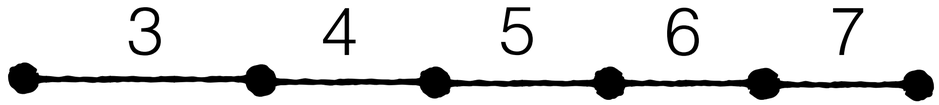


Internal Nodes

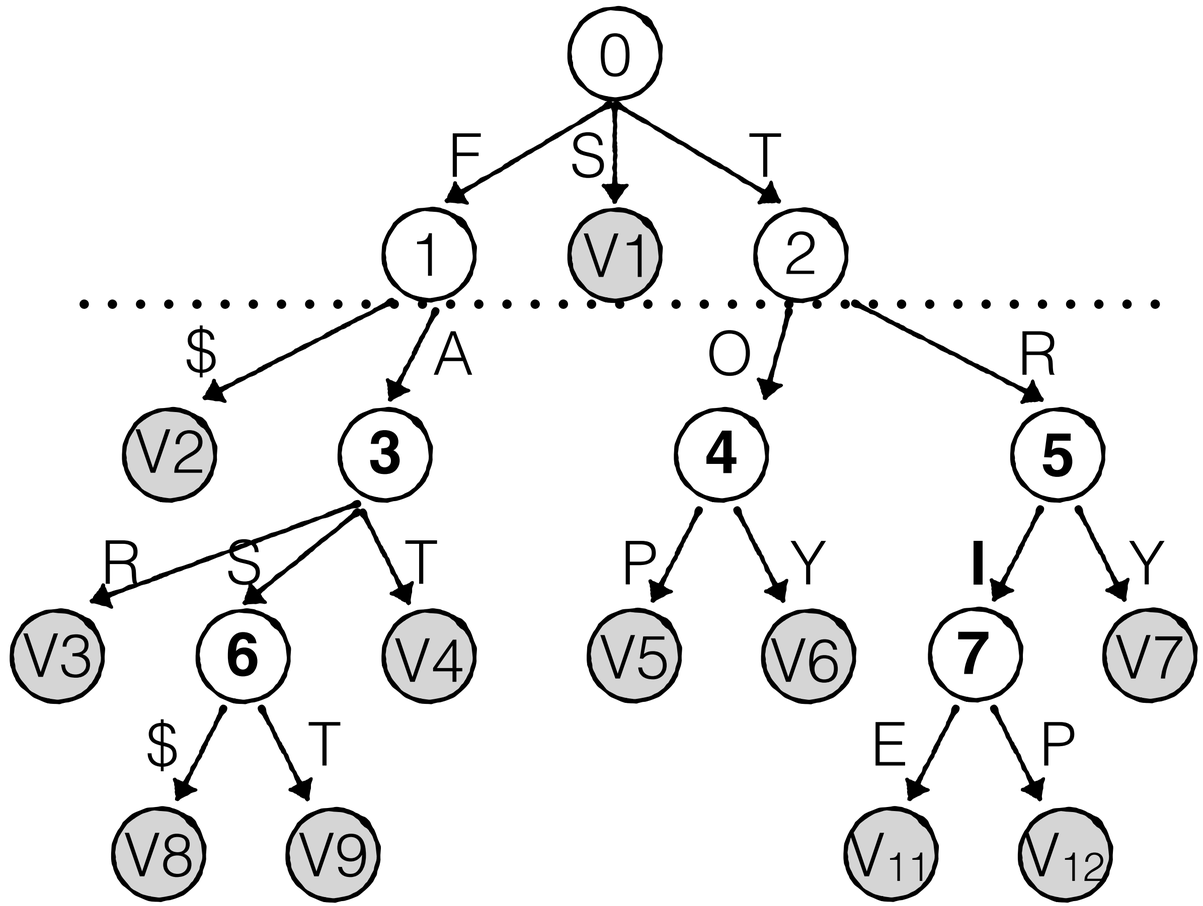
	R	**S**	T	P	Y	**I**	Y	$	T	E	P
Has-child	0	**1**	0	0	0	**1**	0	0	0	0	0



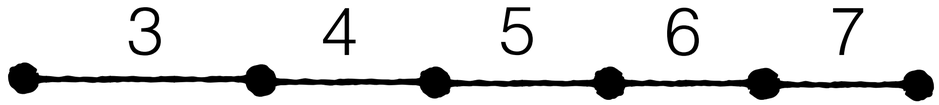
Internal Nodes



	R	S	T	**P**	Y	**I**	Y	**$**	T	**E**	P
Has-child	0	1	0	0	0	1	0	0	0	0	0
LOUDS	**1**	0	0	**1**	0	**1**	0	**1**	0	**1**	0

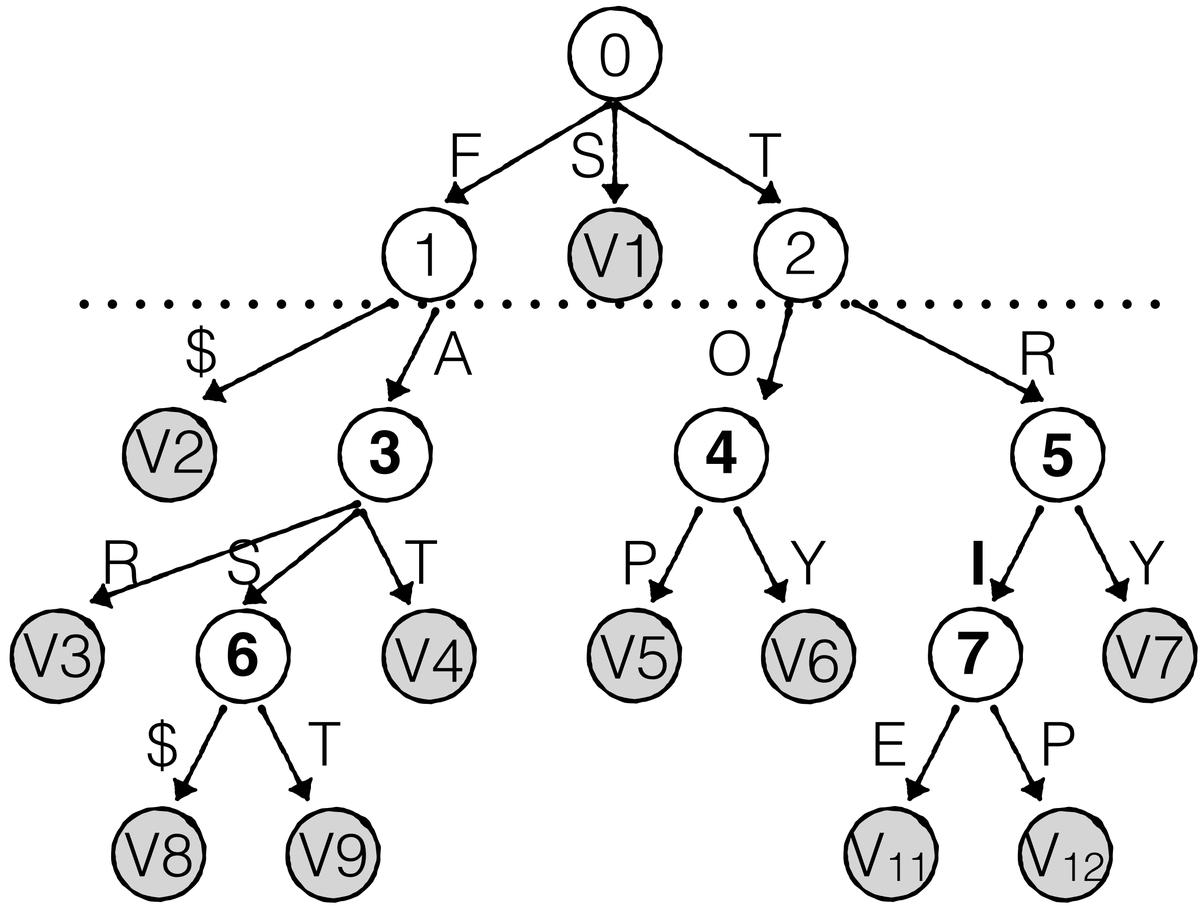


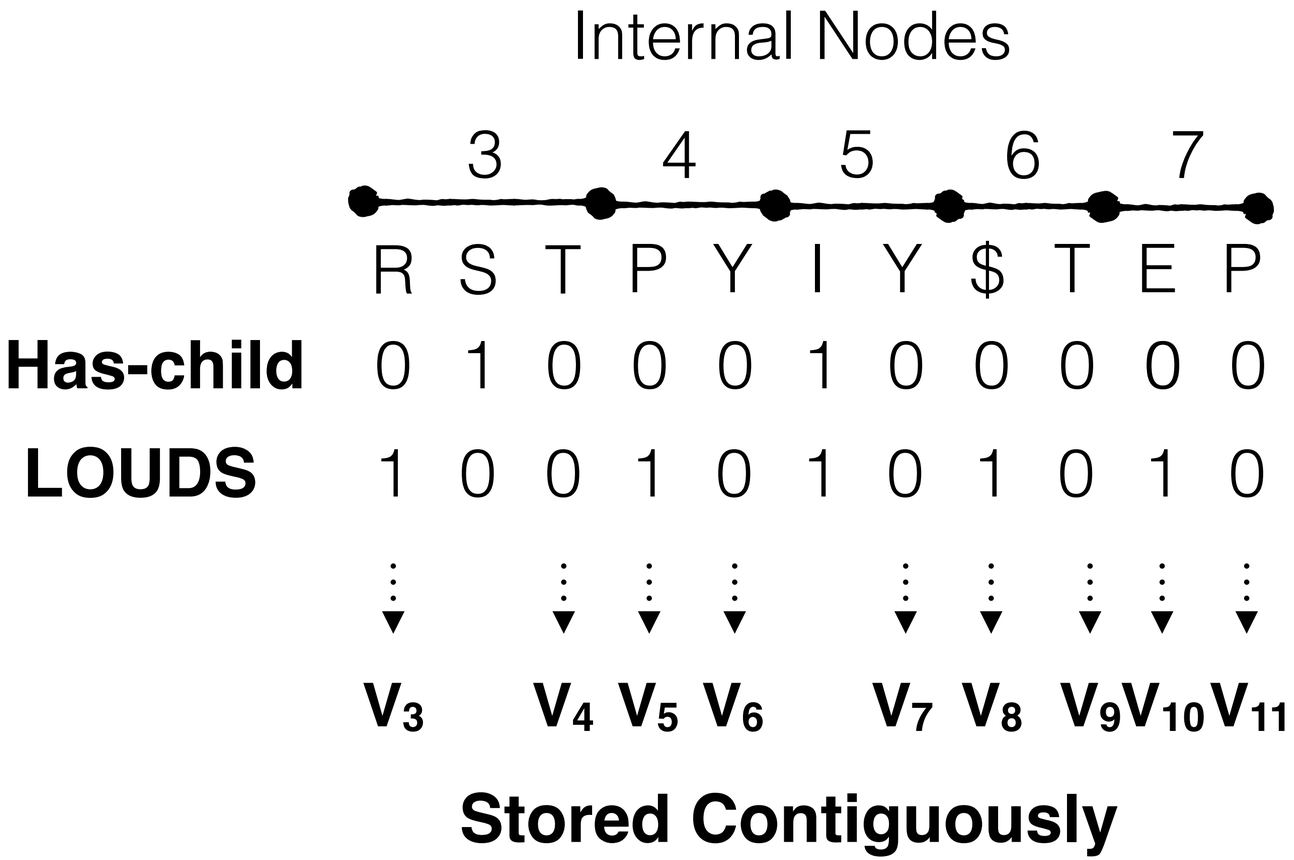
Internal Nodes

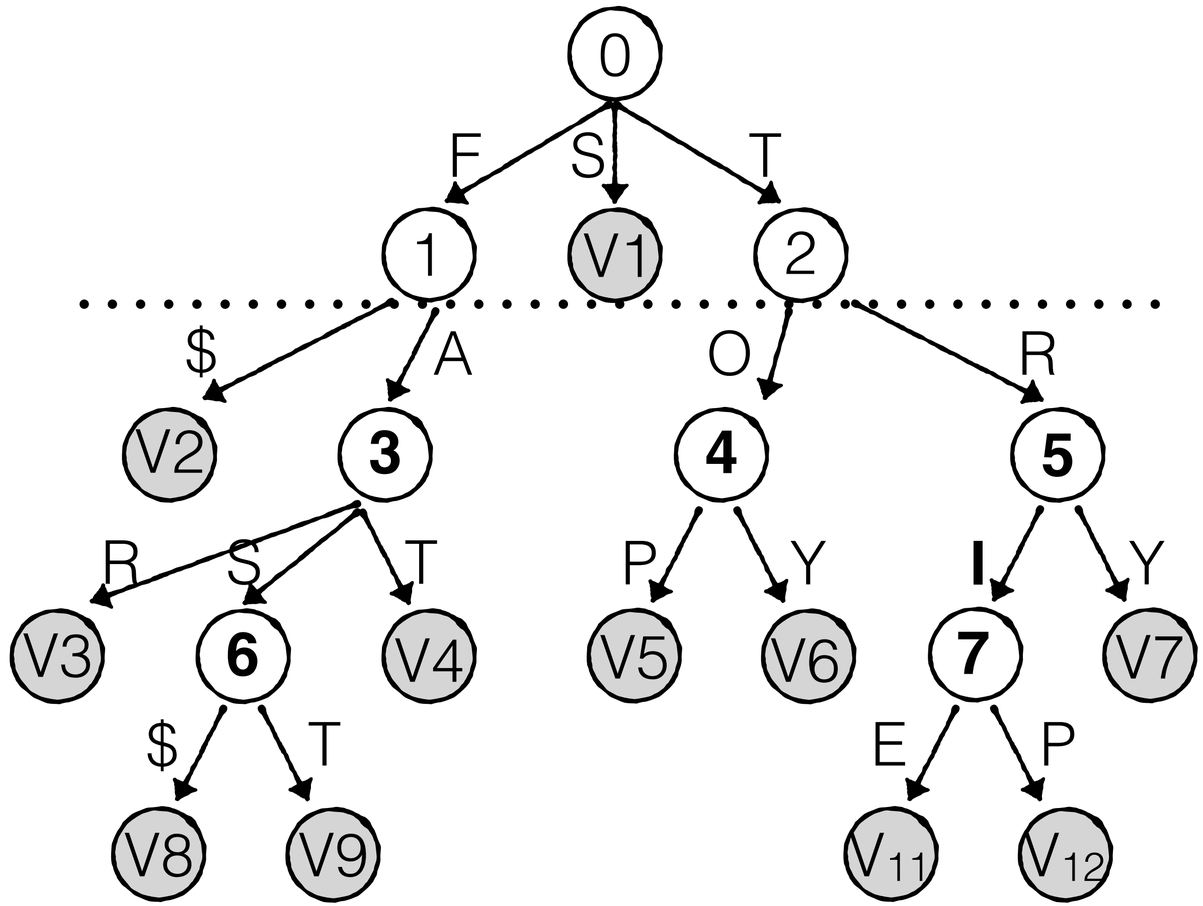


	R	S	T	P	Y	I	Y	$	T	E	P
Has-child	**0**	1	**0**	**0**	**0**	1	**0**	**0**	**0**	**0**	**0**
LOUDS	1	0	0	1	0	1	0	1	0	1	0

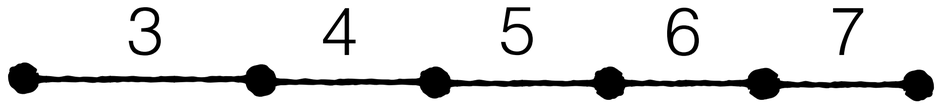
V_3		**V_4**	**V_5**	**V_6**		**V_7**	**V_8**	**V_9**	**V_{10}**	**V_{11}**


0
F
S
T
1
V1
2
$
A
O
R
V2
3
4
5
R
S
T
P
Y
I
Y
V3
6
V4
V5
V6
7
V7
$
T
E
P
V8
V9
V11
V12


Internal Nodes
3
4
5
6
7
R S T P Y I Y $ T E P
Has-child 0 1 0 0 0 1 0 0 0 0 0
LOUDS 1 0 0 1 0 1 0 1 0 1 0
V3 V4 V5 V6 V7 V8 V9 V10 V11
Stored Contiguously



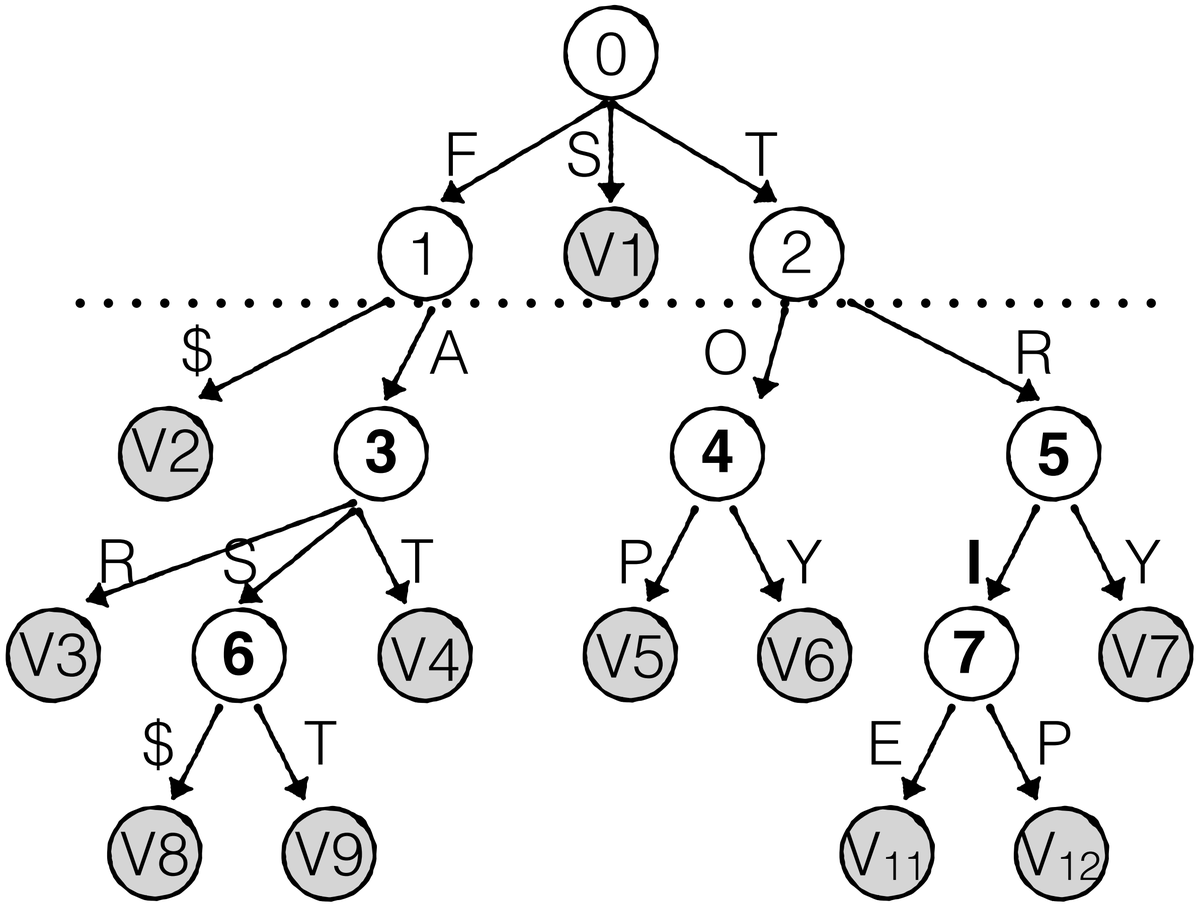
Internal Nodes

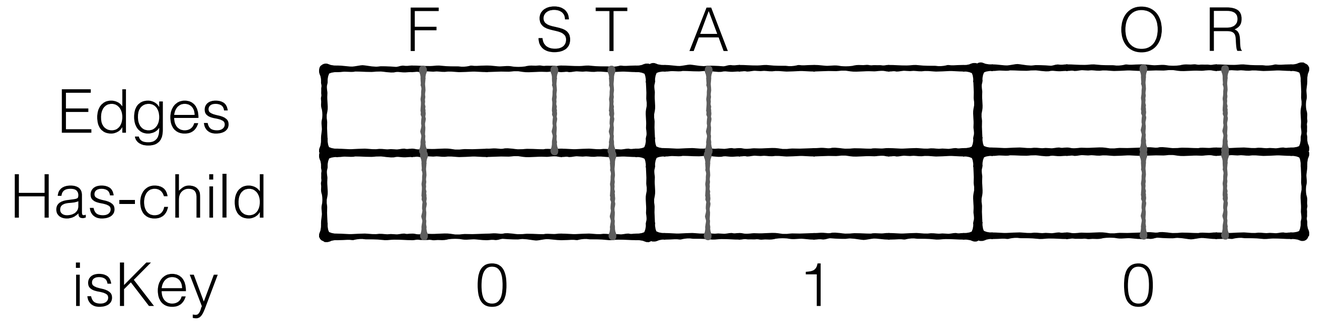


	R	S	T	P	Y	I	Y	$	T	E	P
Has-child	0	1	0	0	0	1	0	0	0	0	0
LOUDS	1	0	0	1	0	1	0	1	0	1	0

V_3 V_4 V_5 V_6 V_7 V_8 V_9 V_{10} V_{11}

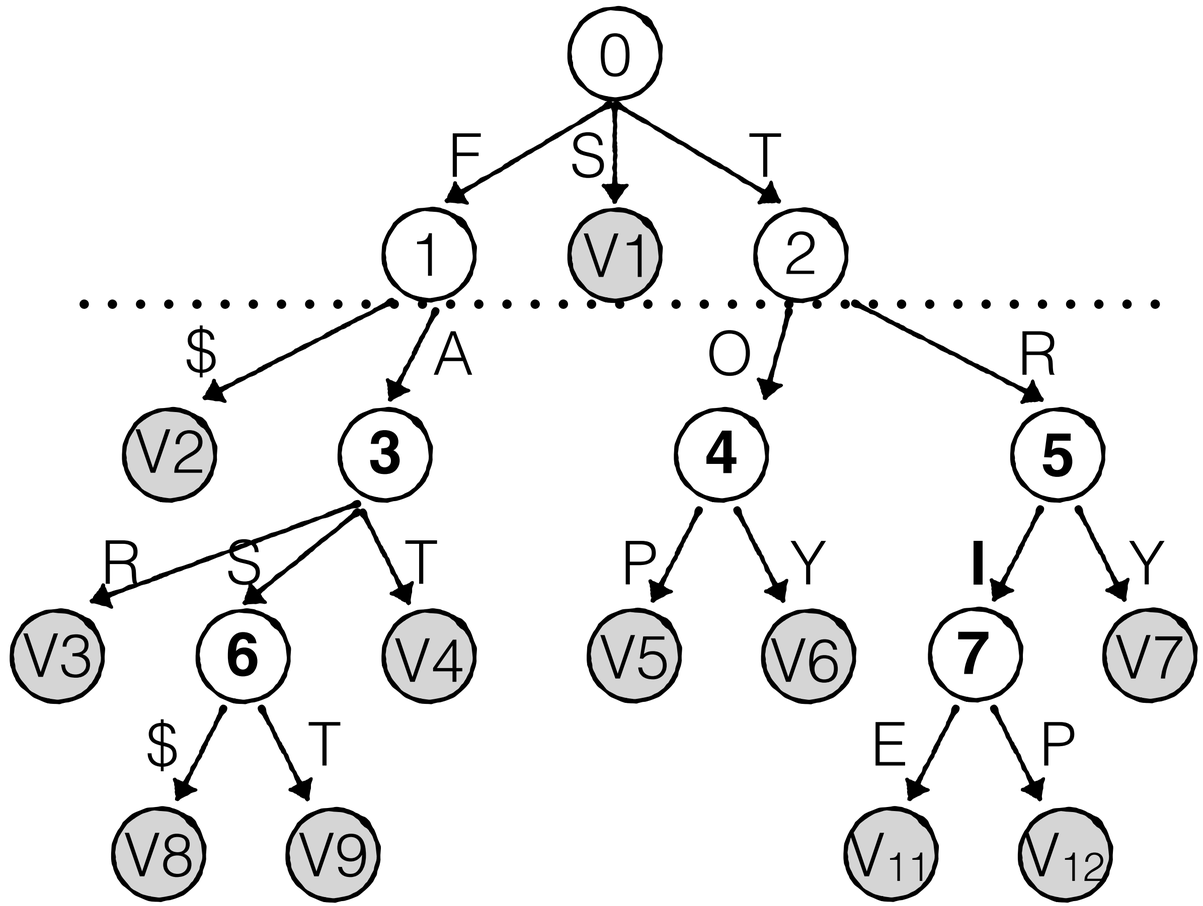
Each leaf connected to payload

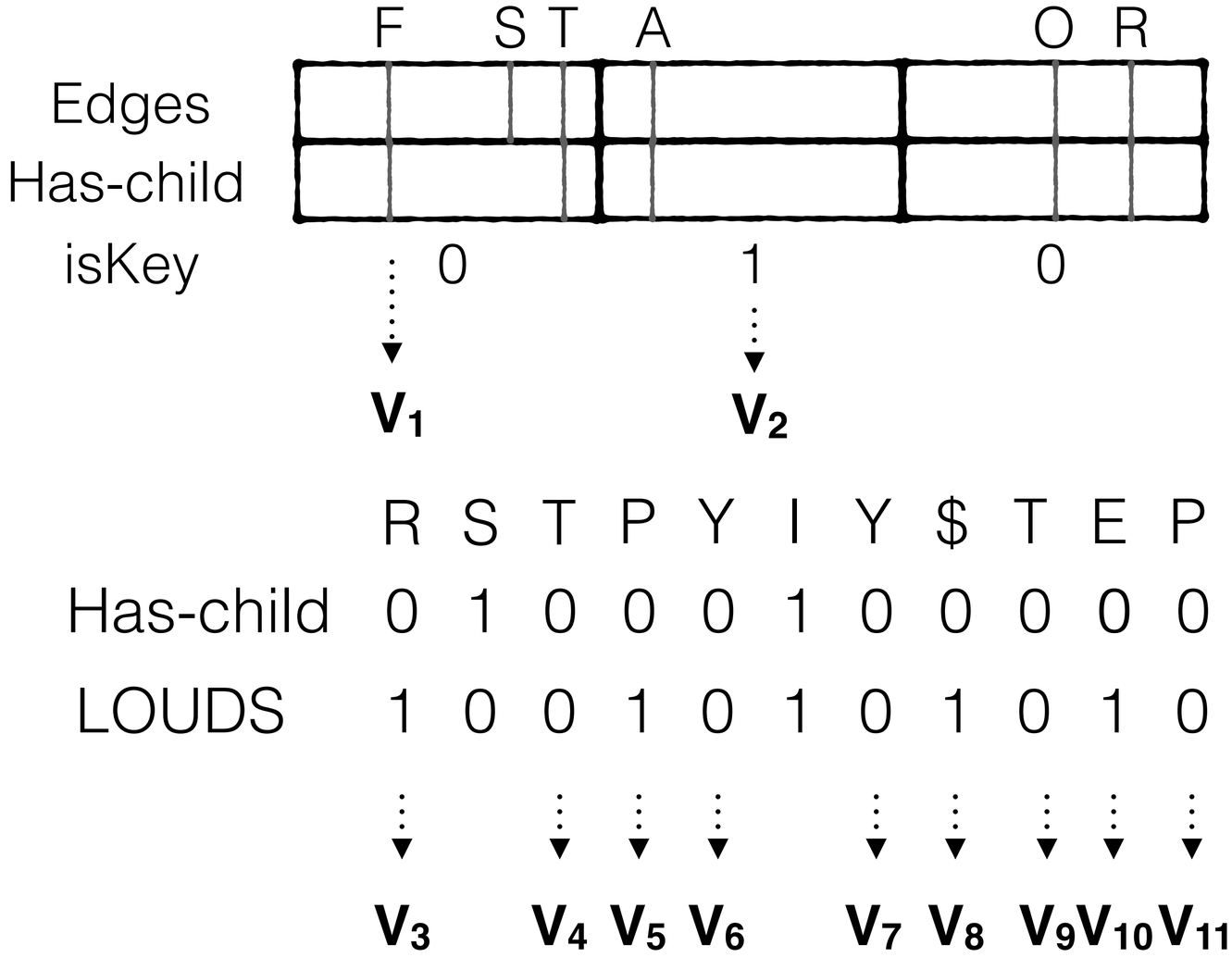


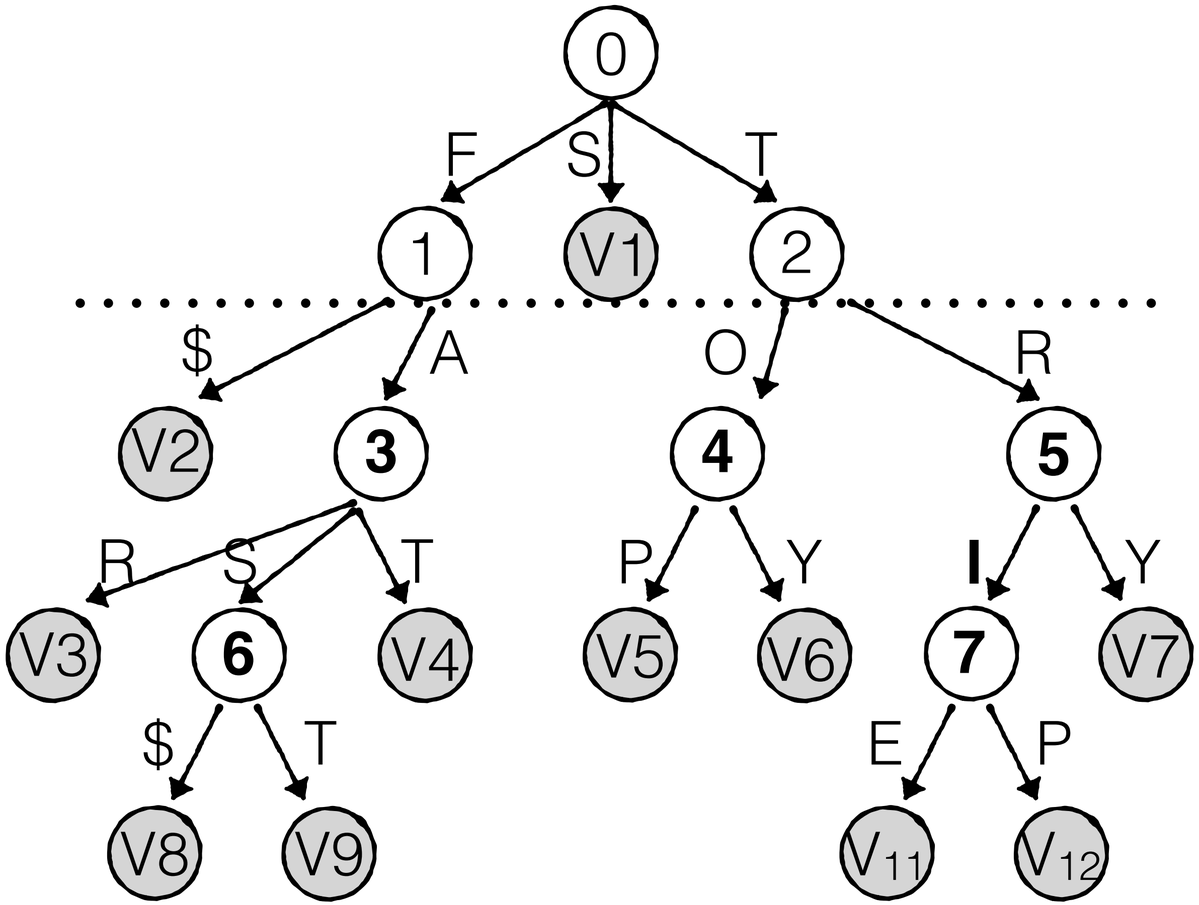


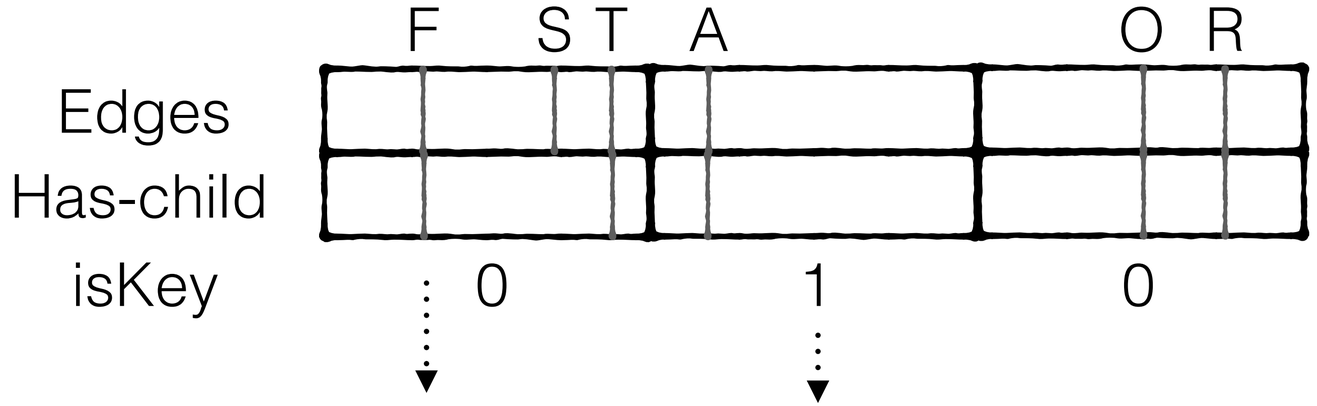
	R	S	T	P	Y	I	Y	$	T	E	P
Has-child	0	1	0	0	0	1	0	0	0	0	0
LOUDS	1	0	0	1	0	1	0	1	0	1	0

Whole filter :)


0
F
S
T
1
V1
2
$
A
O
R
V2
3
4
5
R
S
T
P
Y
I
Y
V3
6
V4
V5
V6
7
V7
$
T
E
P
V8
V9
V11
V12

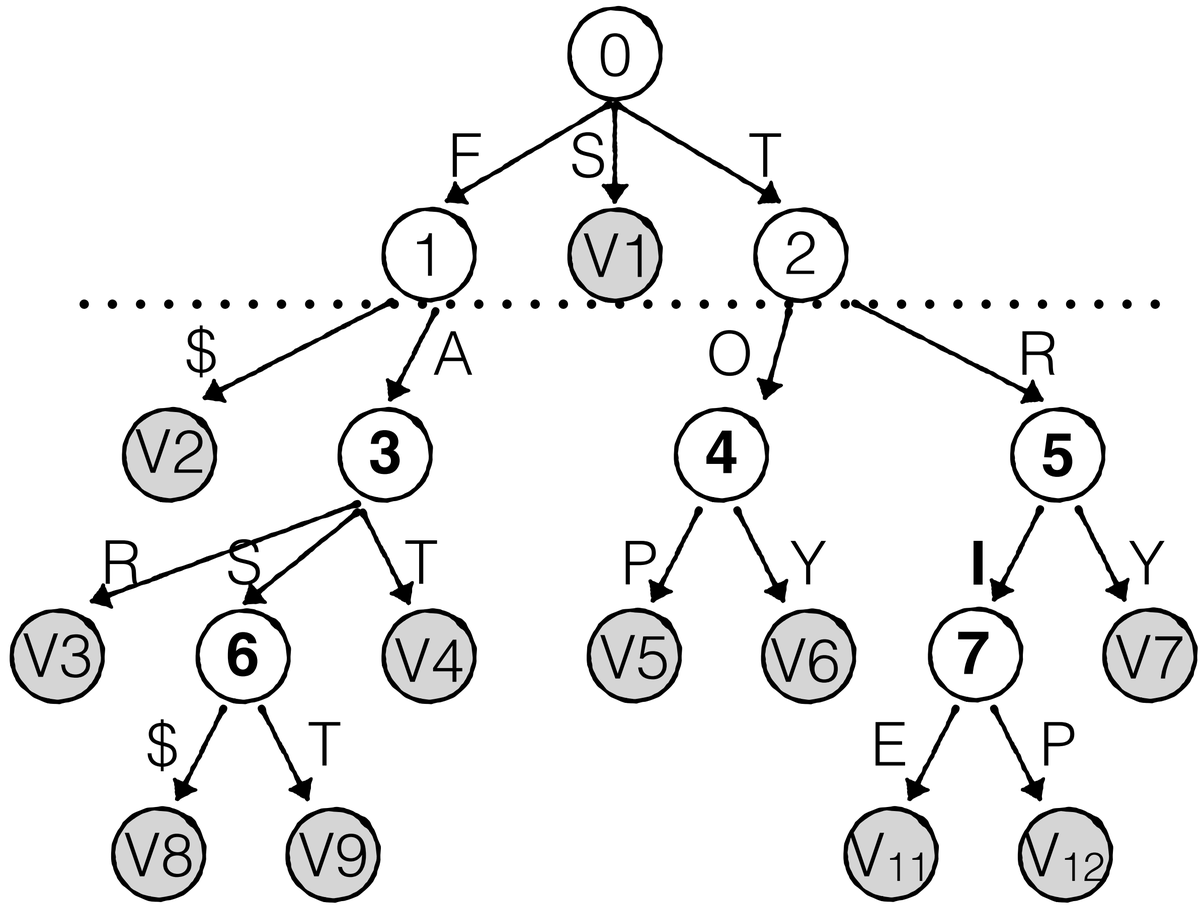

F S T A O R
Edges
Has-child
isKey
0 1 0
V1 V2
R S T P Y I Y $ T E P
Has-child 0 1 0 0 0 1 0 0 0 0 0
LOUDS 1 0 0 1 0 1 0 1 0 1 0
V3 V4 V5 V6 V7 V8 V9 V10 V11



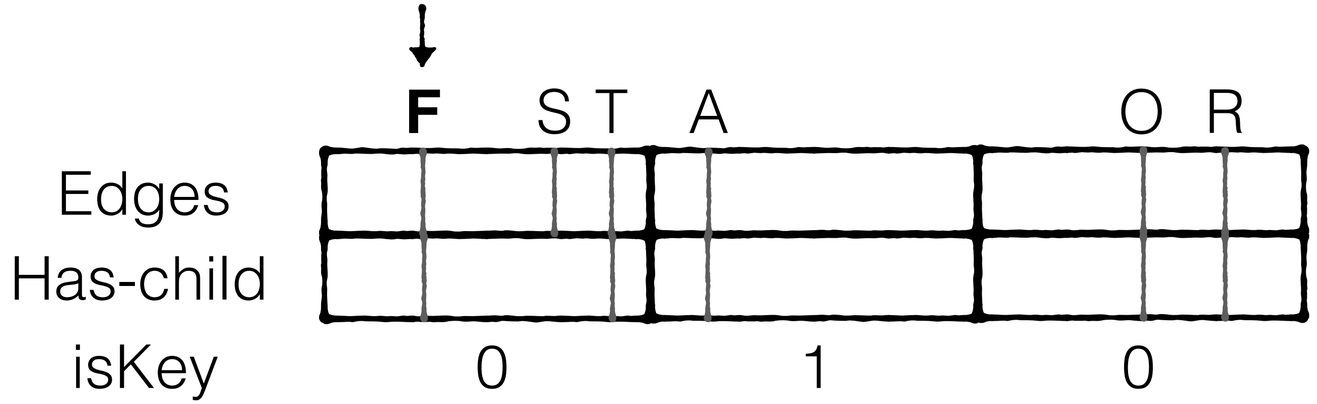


	R	S	T	P	Y	I	Y	$	T	E	P
Has-child	0	1	0	0	0	1	0	0	0	0	0
LOUDS	1	0	0	1	0	1	0	1	0	1	0

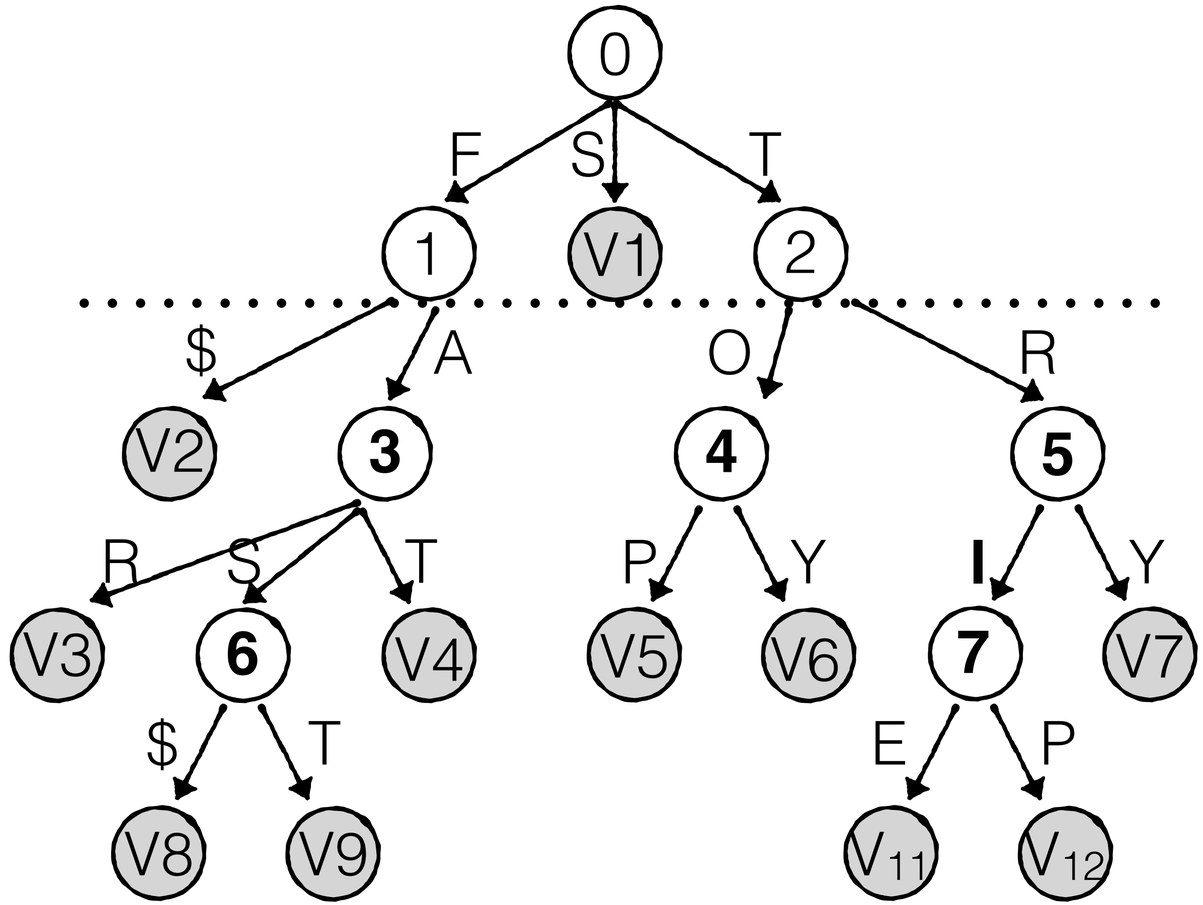
V_1	V_2	V_3	V_4	V_5	V_6	V_7	V_8	V_9	V_{10}	V_{11}

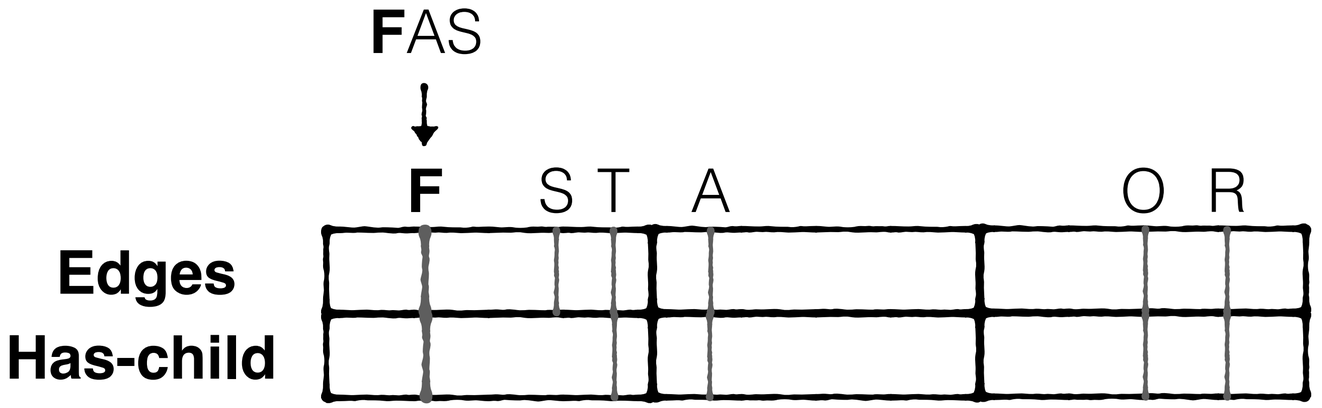


Does “FAS” exist?

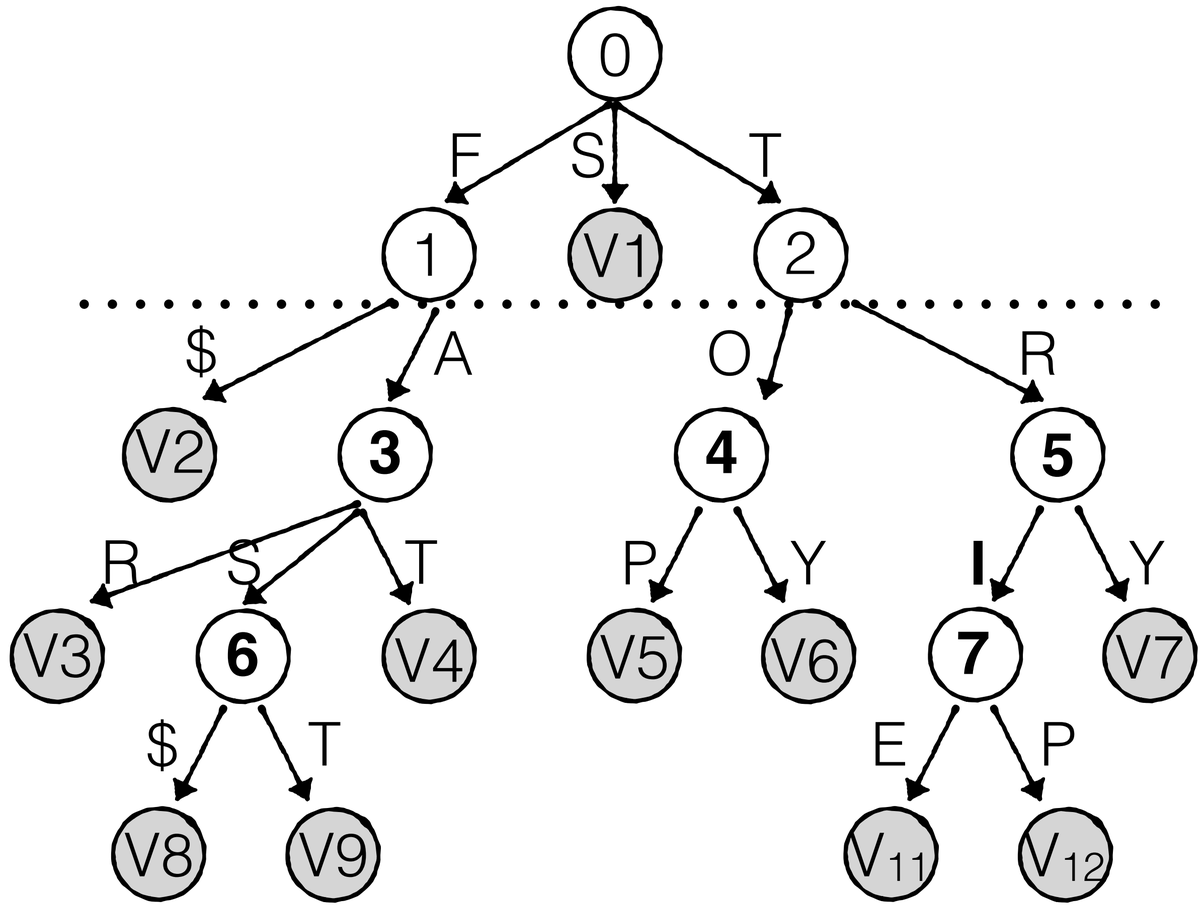


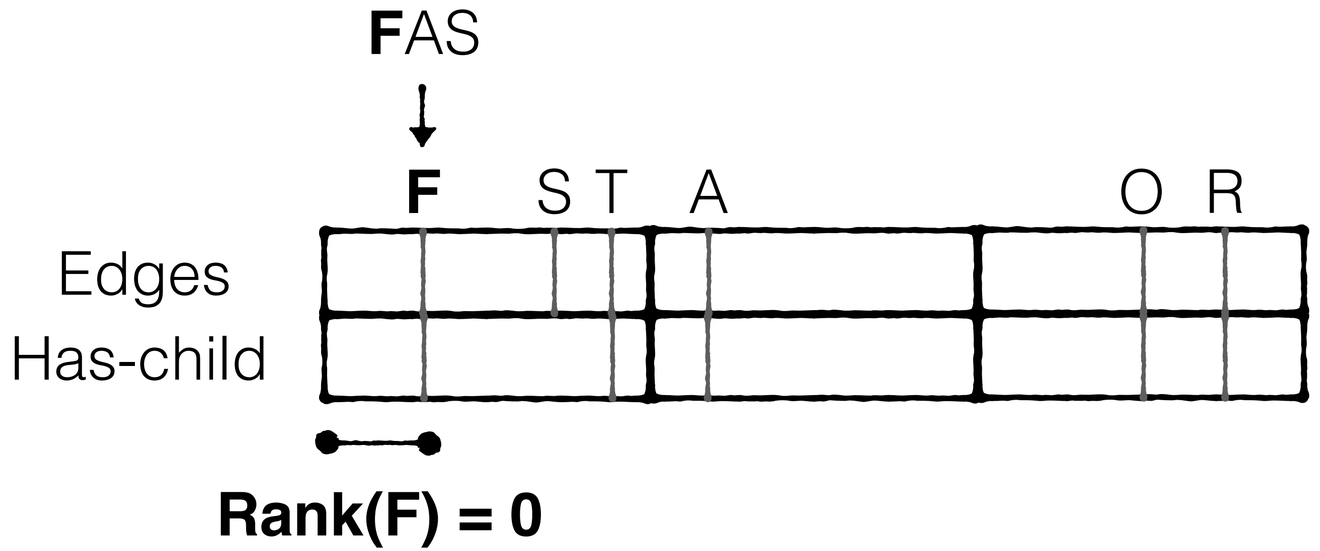
	R	S	T	P	Y	I	Y	$	T	E	P
Has-child	0	1	0	0	0	1	0	0	0	0	0
LOUDS	1	0	0	1	0	1	0	1	0	1	0



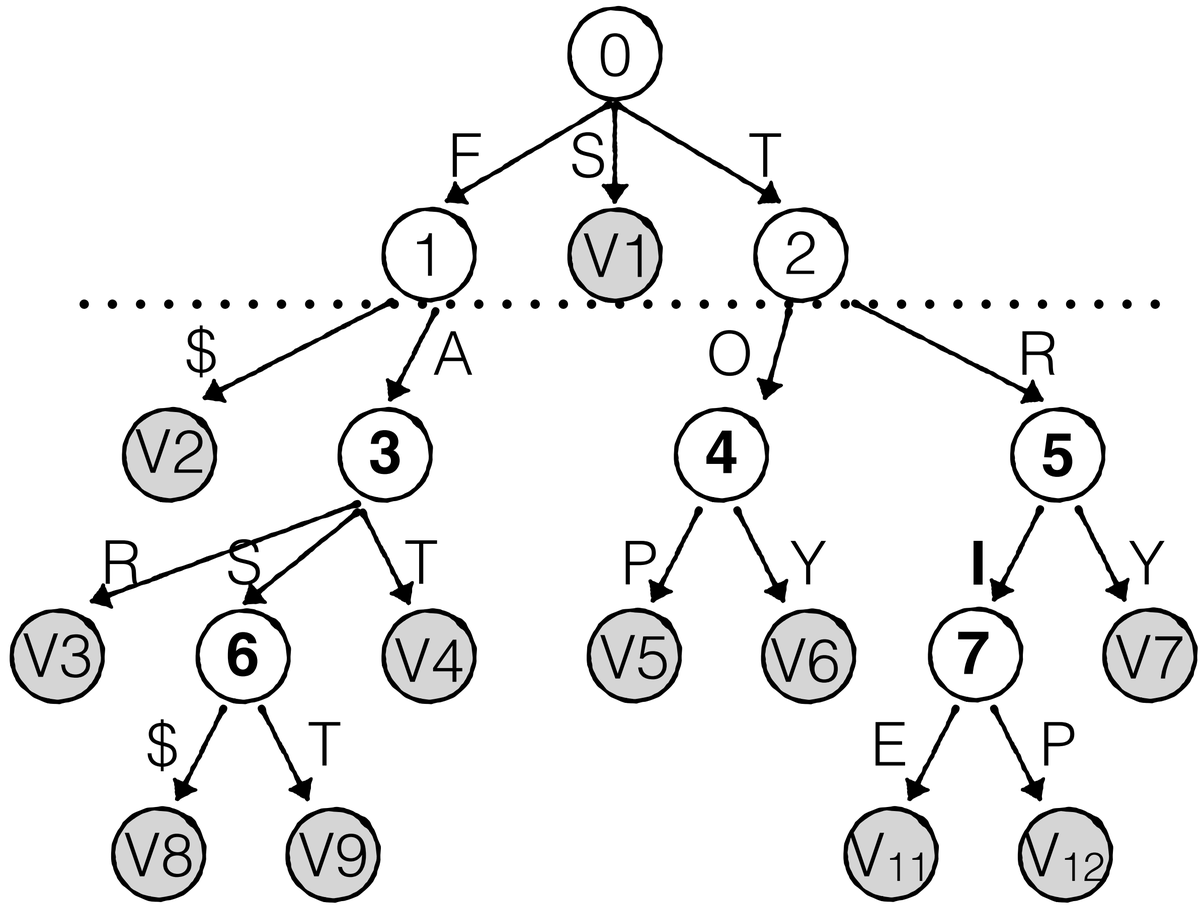


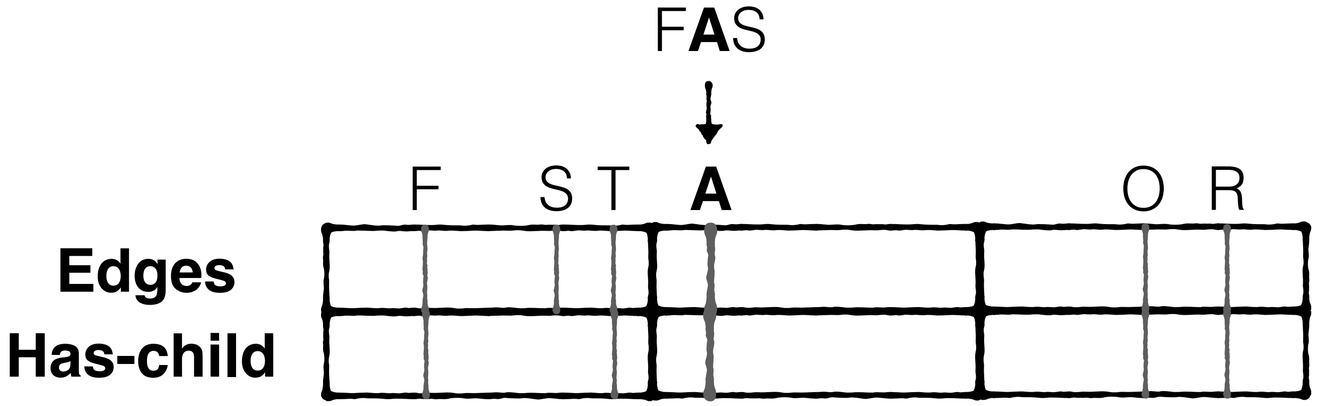
	R	S	T	P	Y	I	Y	$	T	E	P
Has-child	0	1	0	0	0	1	0	0	0	0	0
LOUDS	1	0	0	1	0	1	0	1	0	1	0



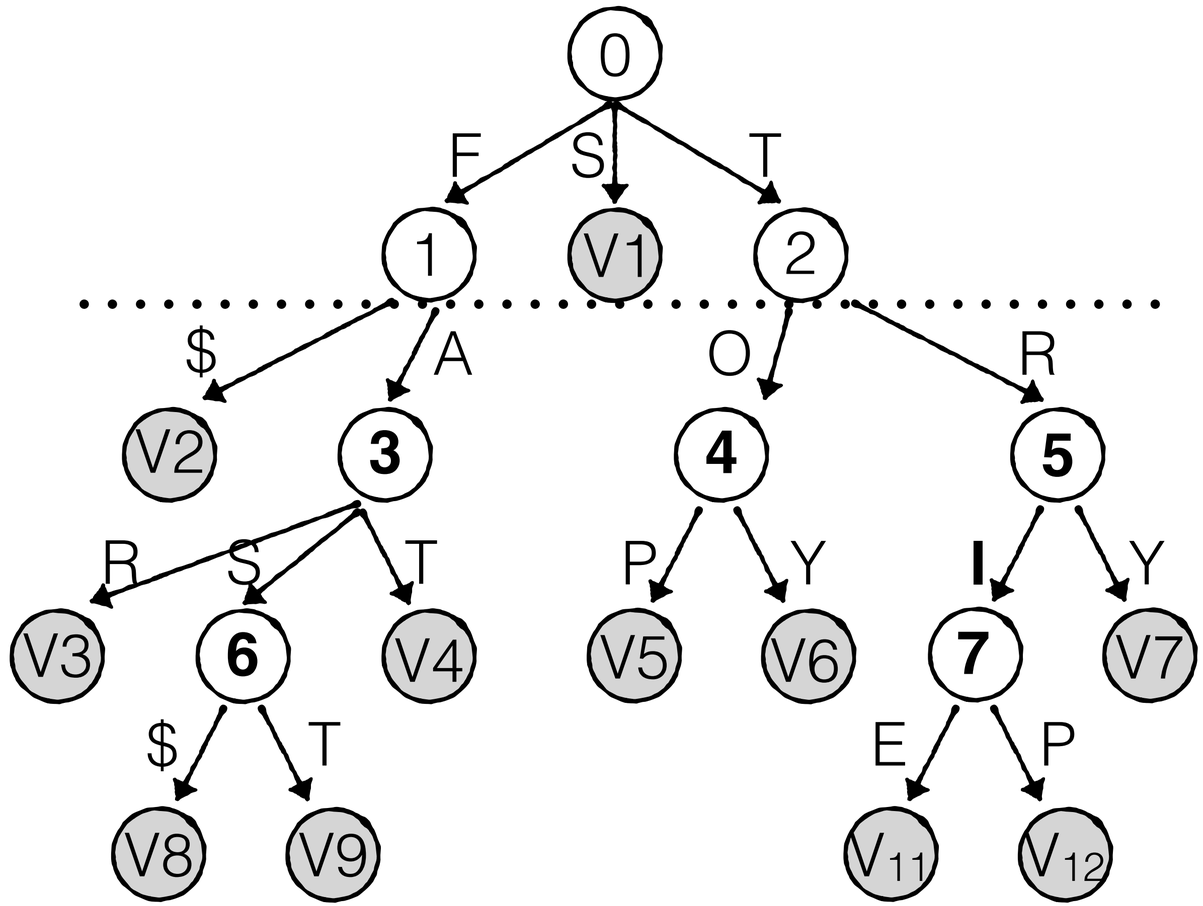


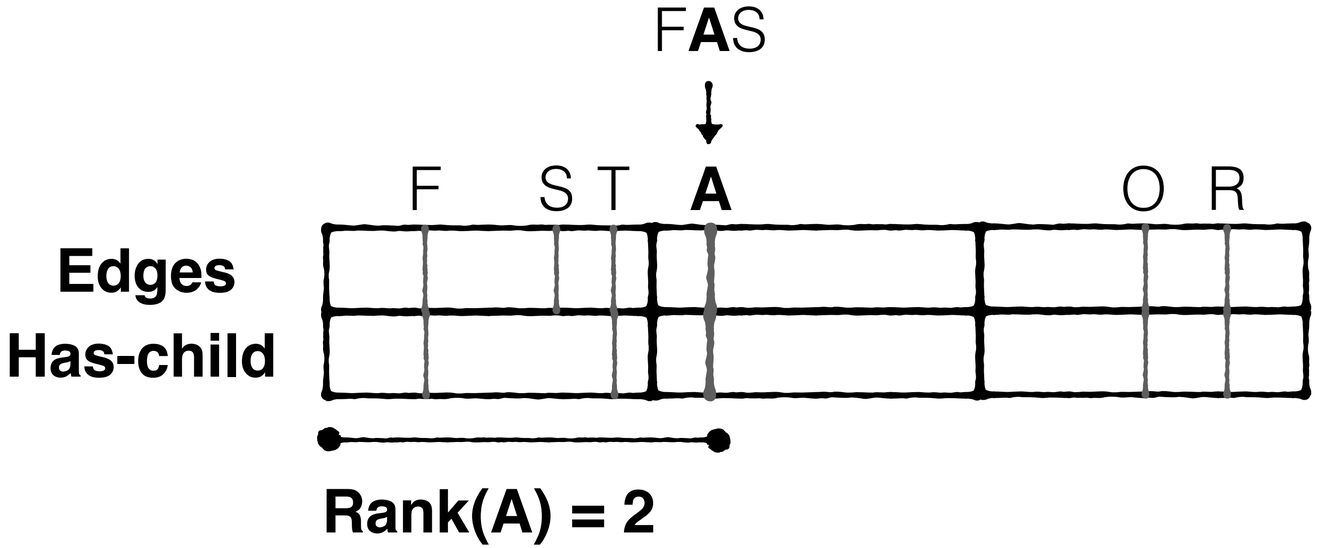
	R	S	T	P	Y	I	Y	$	T	E	P
Has-child	0	1	0	0	0	1	0	0	0	0	0
LOUDS	1	0	0	1	0	1	0	1	0	1	0



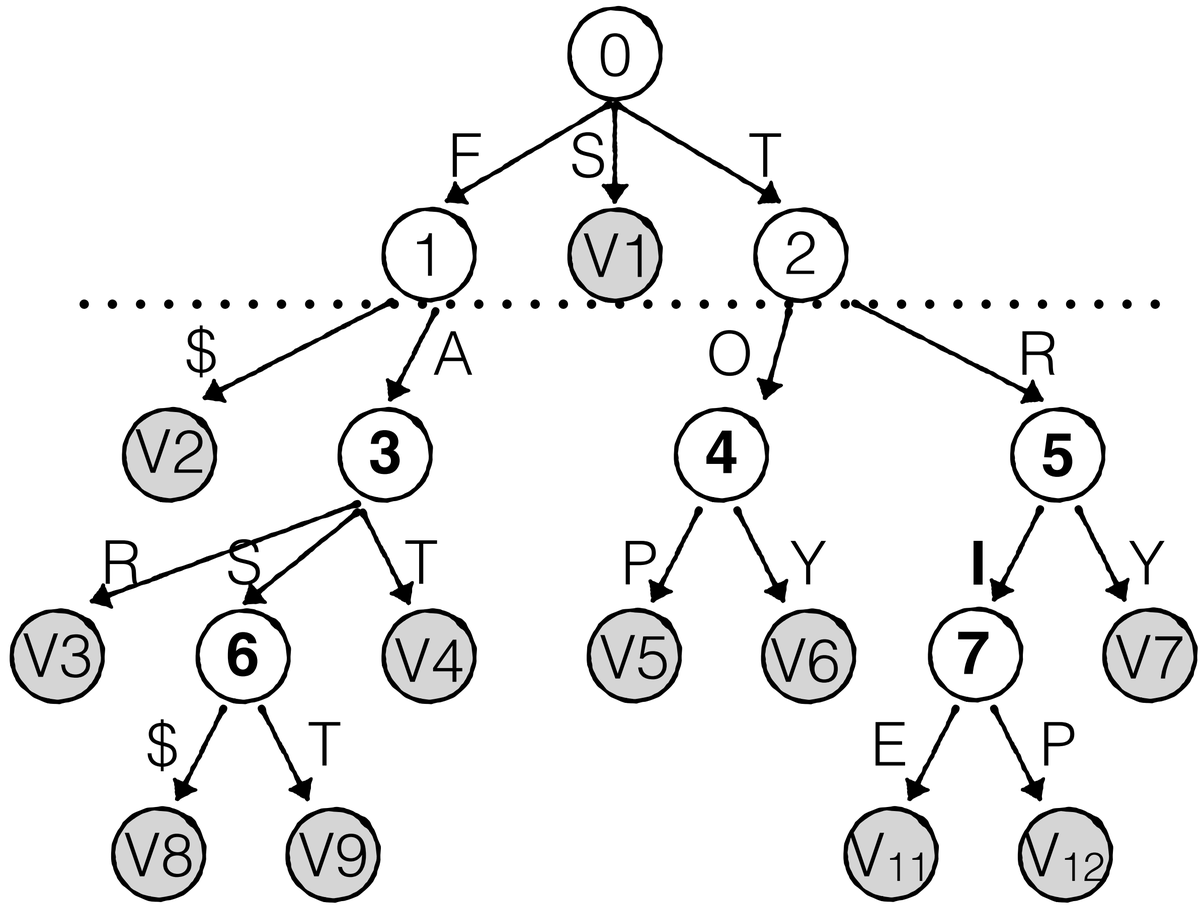


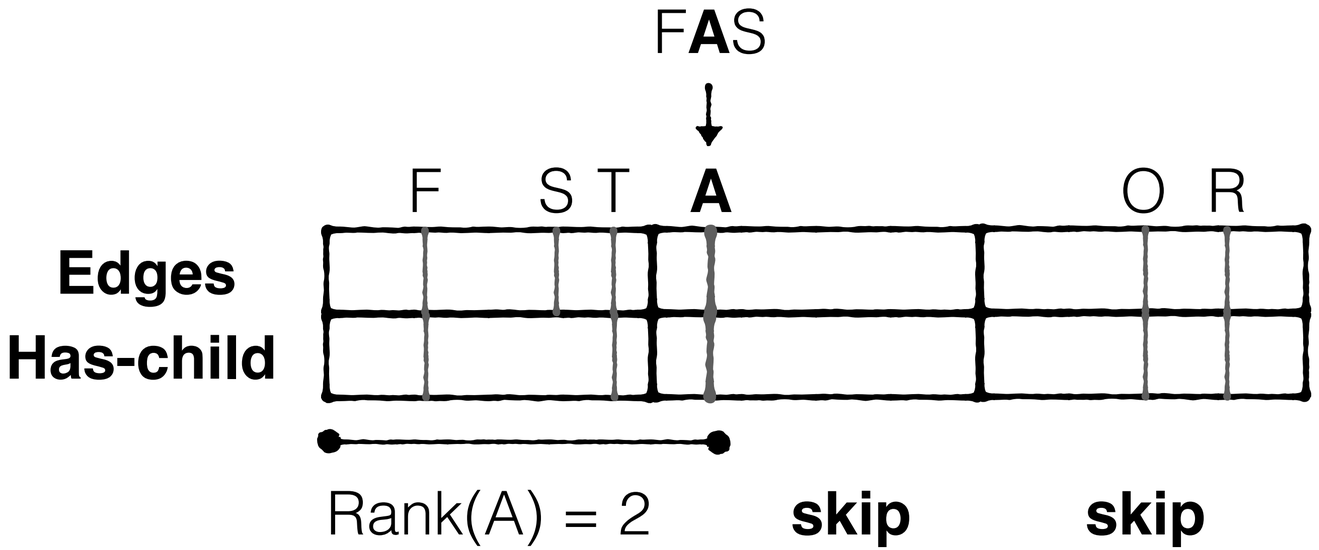
	R	S	T	P	Y	I	Y	$	T	E	P
Has-child	0	1	0	0	0	1	0	0	0	0	0
LOUDS	1	0	0	1	0	1	0	1	0	1	0



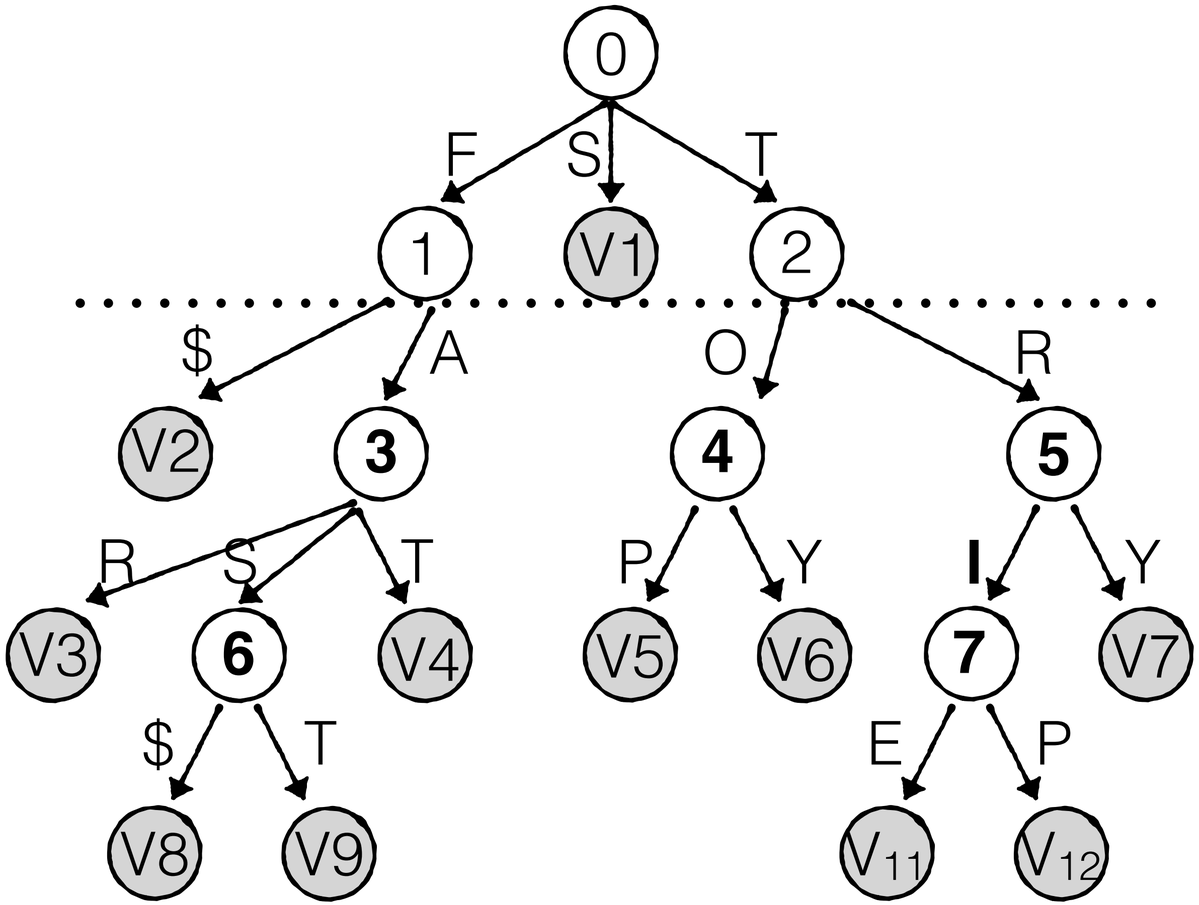


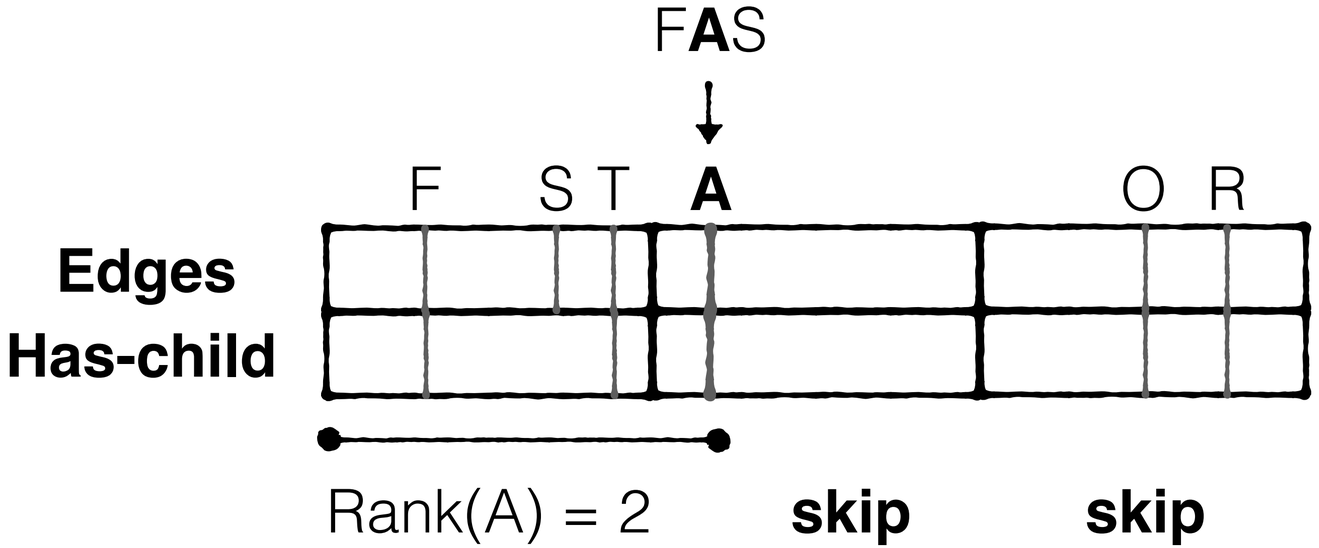
	R	S	T	P	Y	I	Y	$	T	E	P
Has-child	0	1	0	0	0	1	0	0	0	0	0
LOUDS	1	0	0	1	0	1	0	1	0	1	0





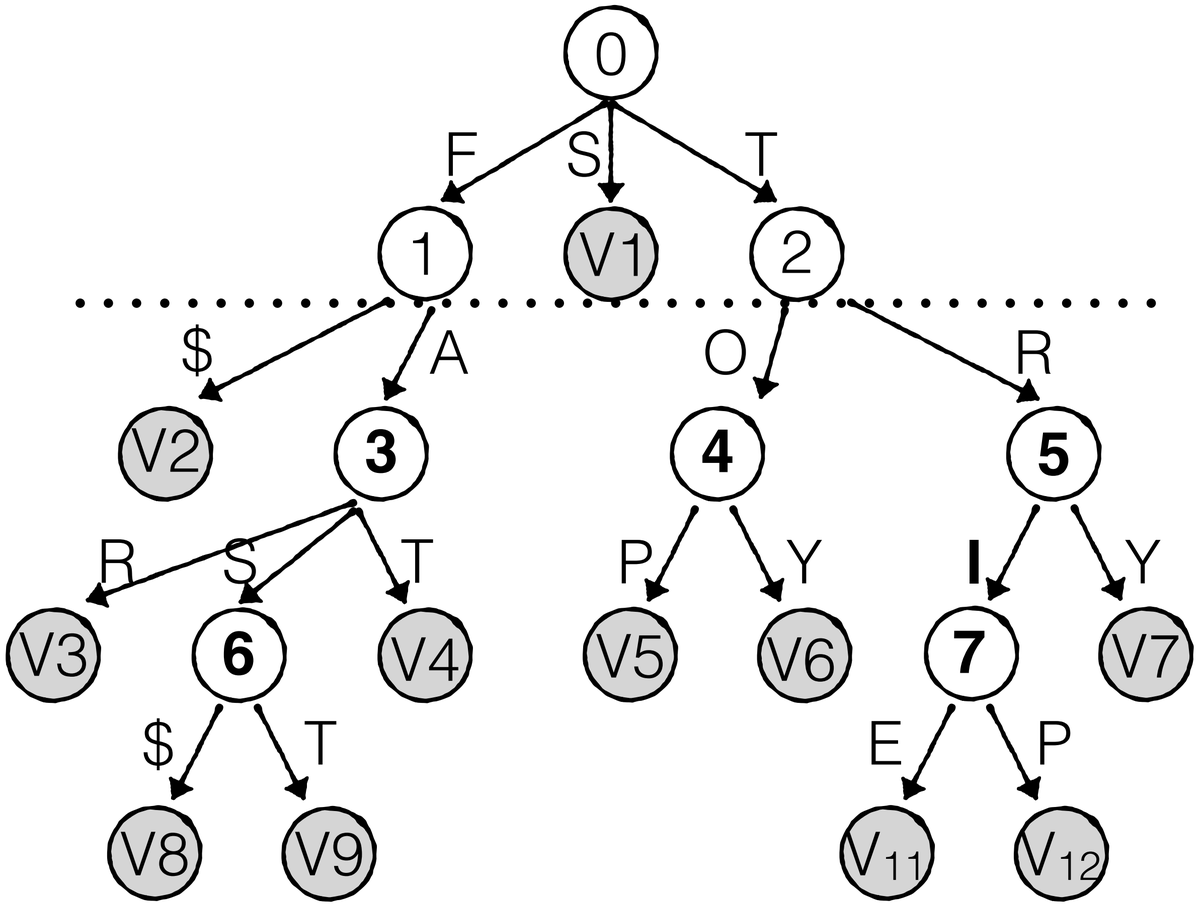
	R	S	T	P	Y	I	Y	$	T	E	P
Has-child	0	1	0	0	0	1	0	0	0	0	0
LOUDS	1	0	0	1	0	1	0	1	0	1	0

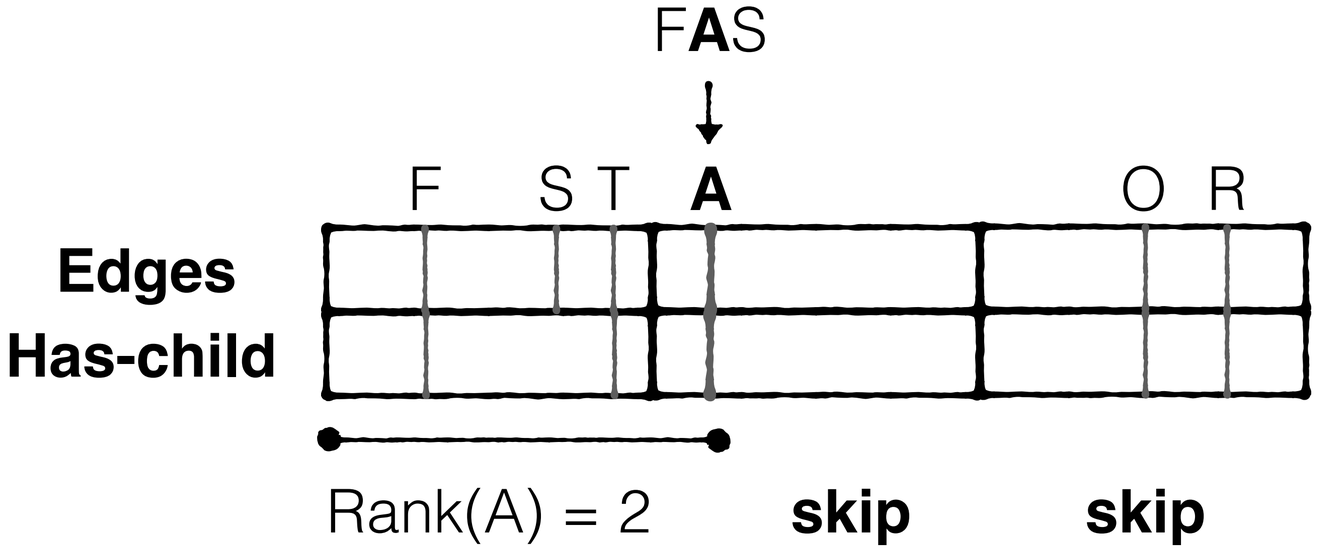




	R	S	T	P	Y	I	Y	$	T	E	P
Has-child	0	1	0	0	0	1	0	0	0	0	0
LOUDS	**1**	**0**	**0**	**1**	**0**	**1**	**0**	**1**	**0**	**1**	**0**

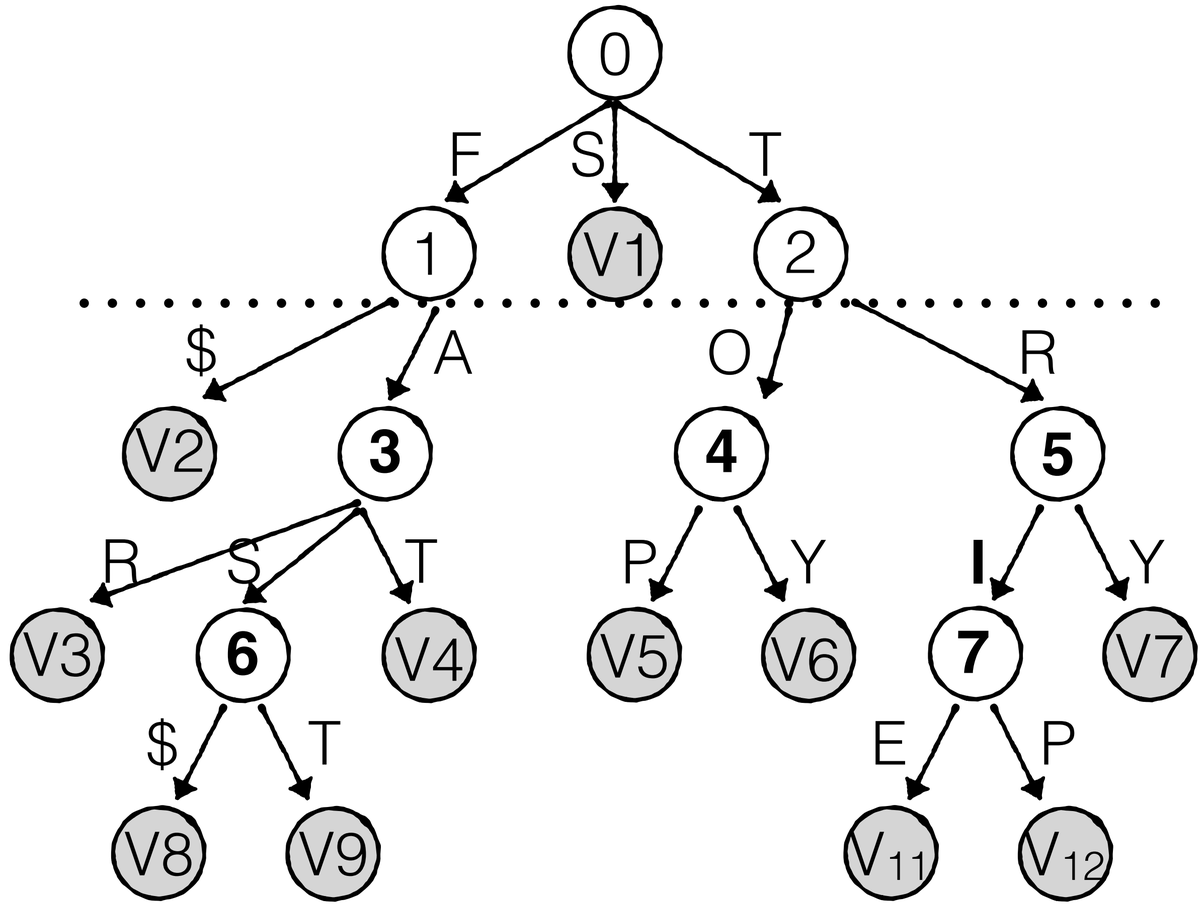
Select(2 - #dense nodes - 1)

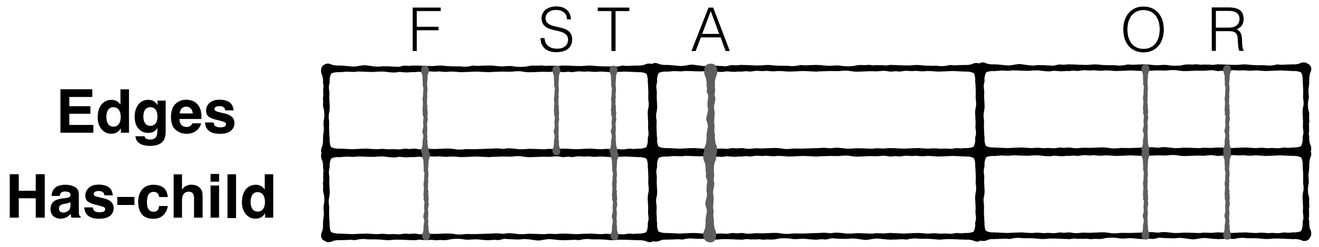




	R	S	T	P	Y	I	Y	$	T	E	P
Has-child	0	1	0	0	0	1	0	0	0	0	0
LOUDS	**1**	**0**	**0**	**1**	**0**	**1**	**0**	**1**	**0**	**1**	**0**

Select(0) = 0

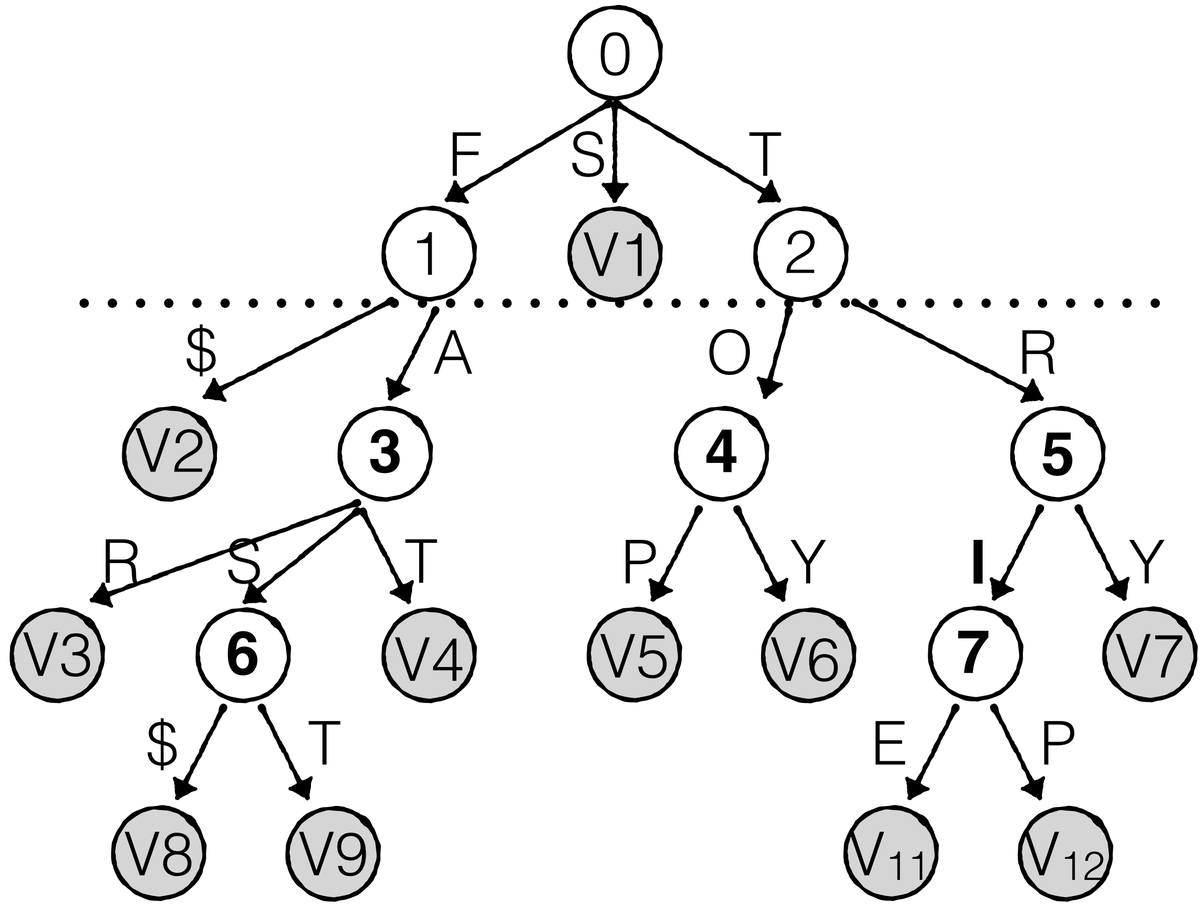


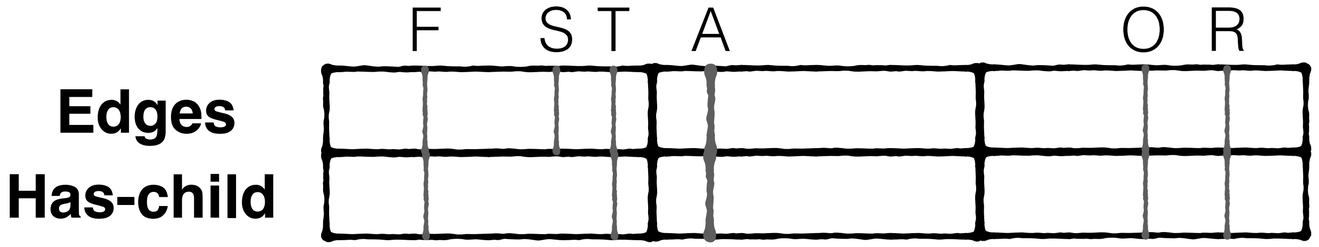


Node 3

	R	**S**	**T**	P	Y	I	Y	$	T	E	P
Has-child	0	1	0	0	0	1	0	0	0	0	0
LOUDS	**1**	0	0	1	0	1	0	1	0	1	0

FA**S**



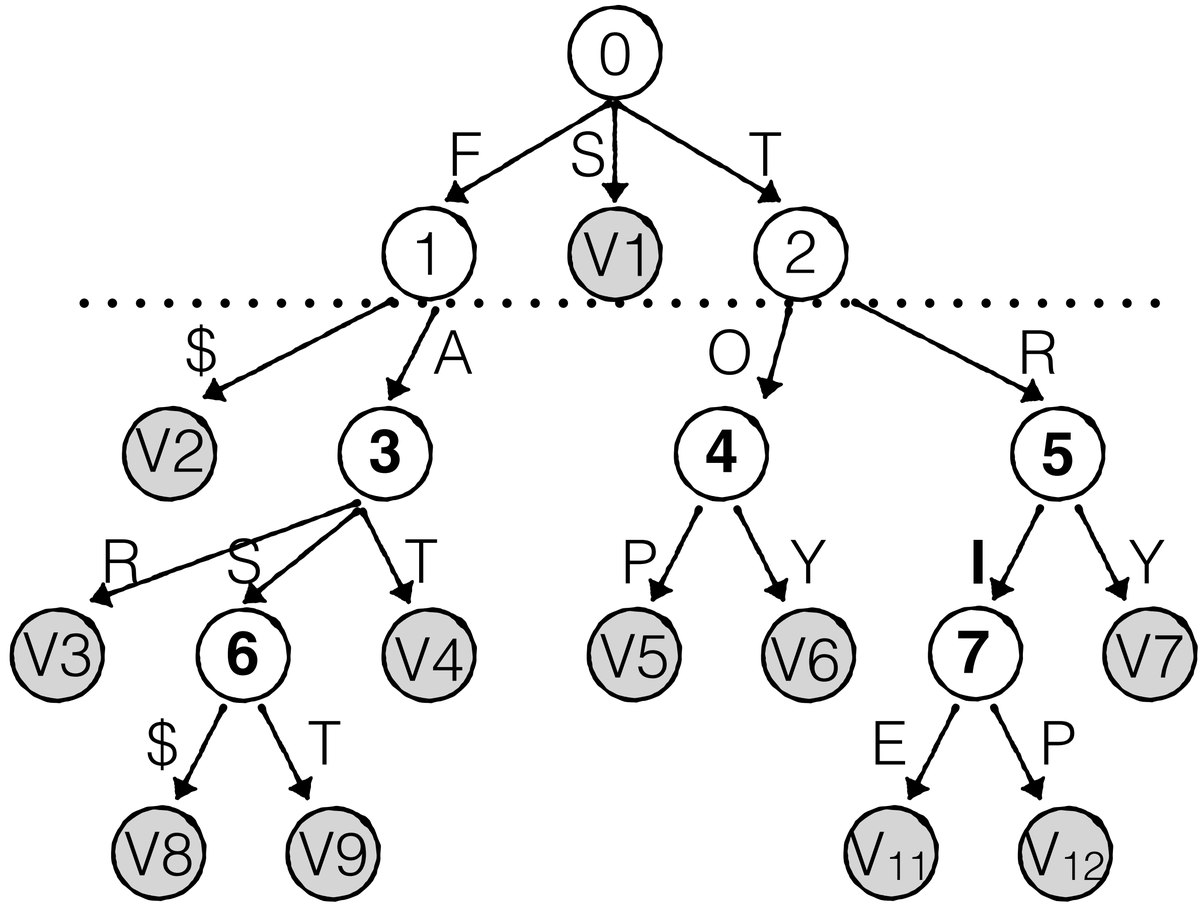


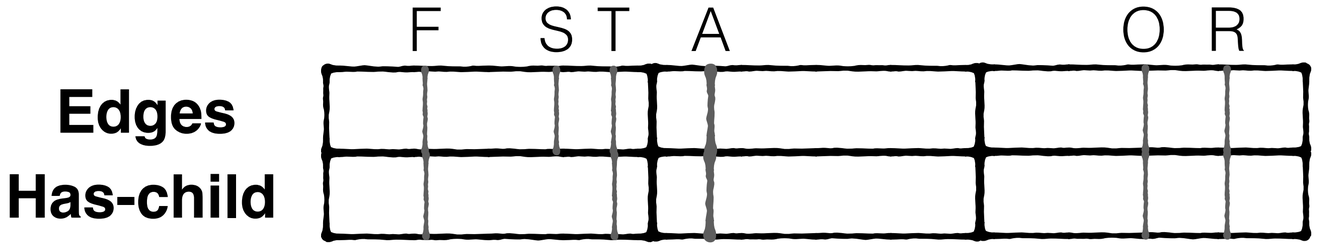
Node 3

	R	**S**	T	P	Y	I	Y	$	T	E	P
Has-child	0	1	0	0	0	1	0	0	0	0	0
LOUDS	1	0	0	1	0	1	0	1	0	1	0

FA**S**

Scan

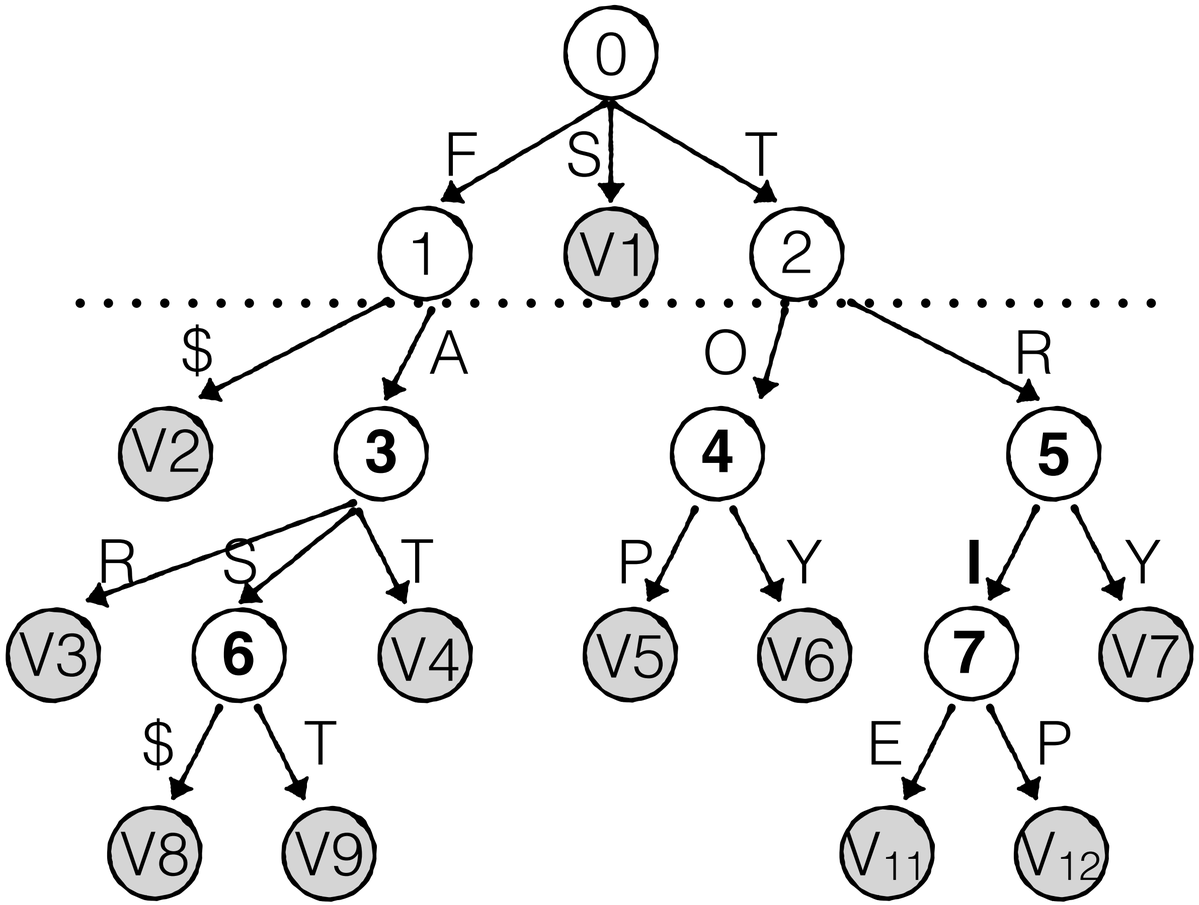


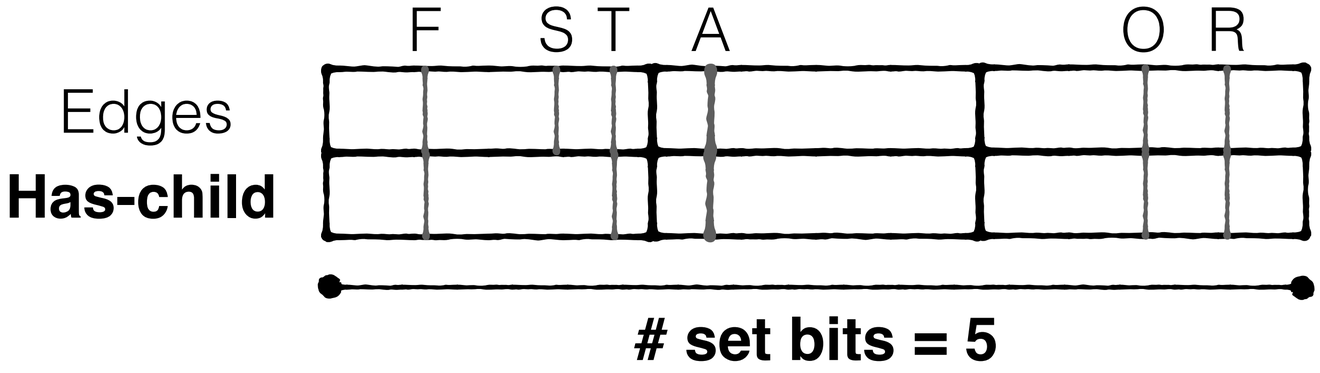


Node 3

	R	**S**	T	P	Y	I	Y	$	T	E	P
Has-child	0	**1**	0	0	0	1	0	0	0	0	0
LOUDS	1	**0**	0	1	0	1	0	1	0	1	0

FA**S**

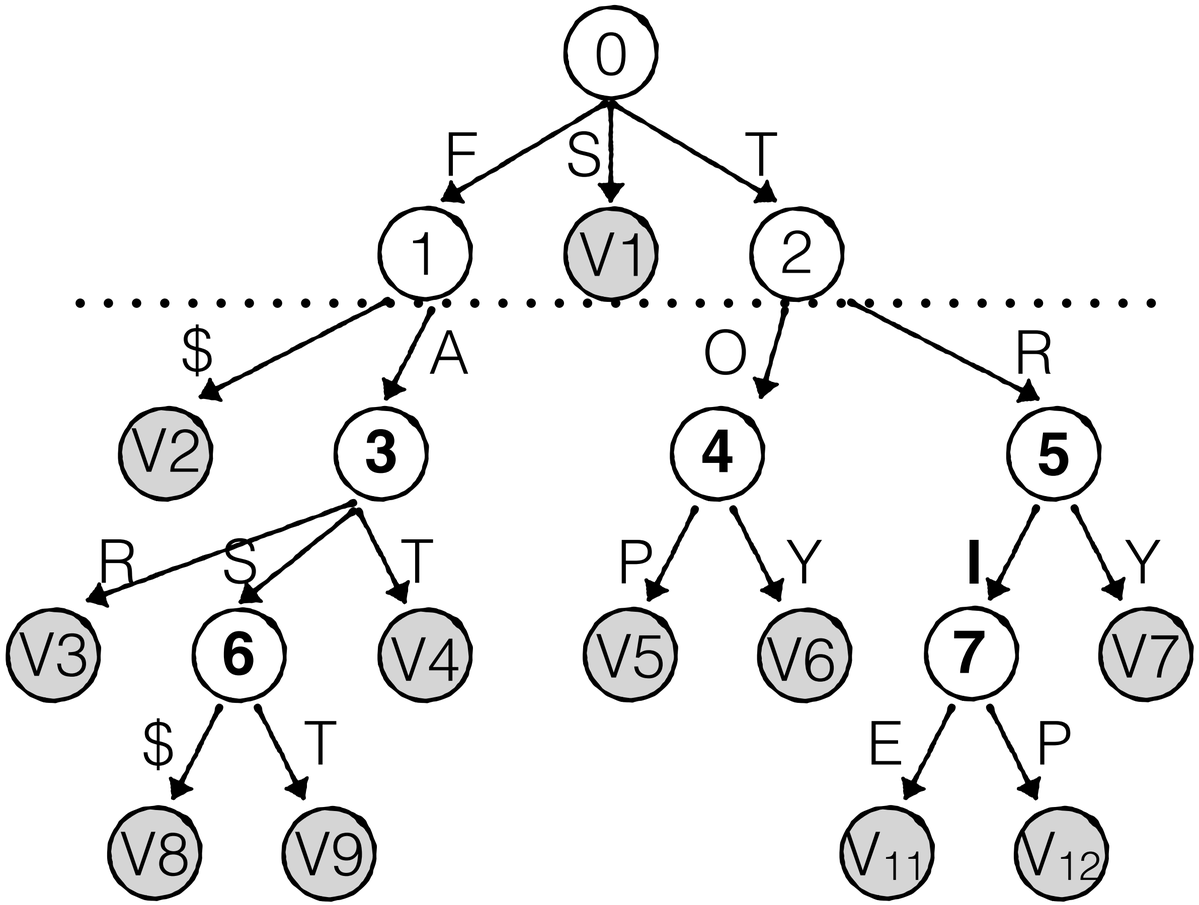


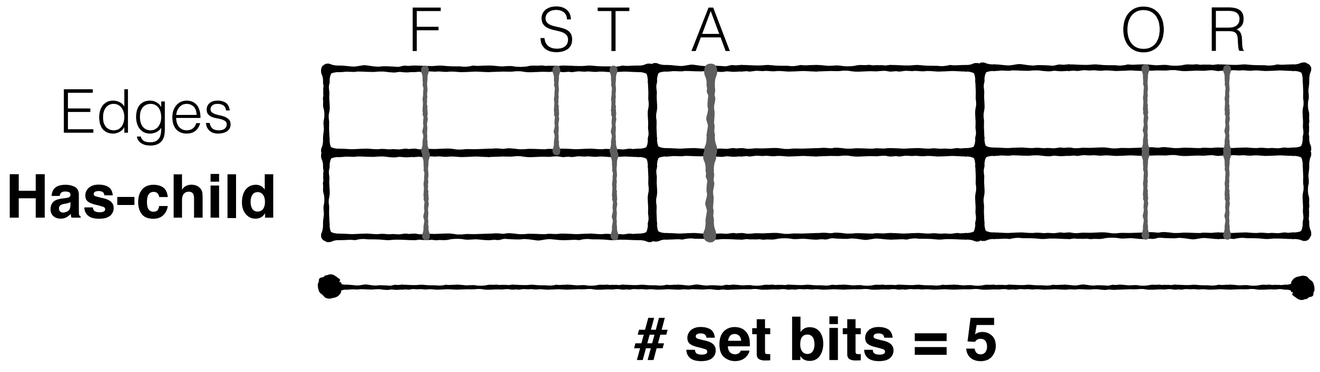


Node 3

	R	**S**	T	P	Y	I	Y	$	T	E	P
Has-child	0	**1**	0	0	0	1	0	0	0	0	0
LOUDS	1	**0**	0	1	0	1	0	1	0	1	0

FA**S**

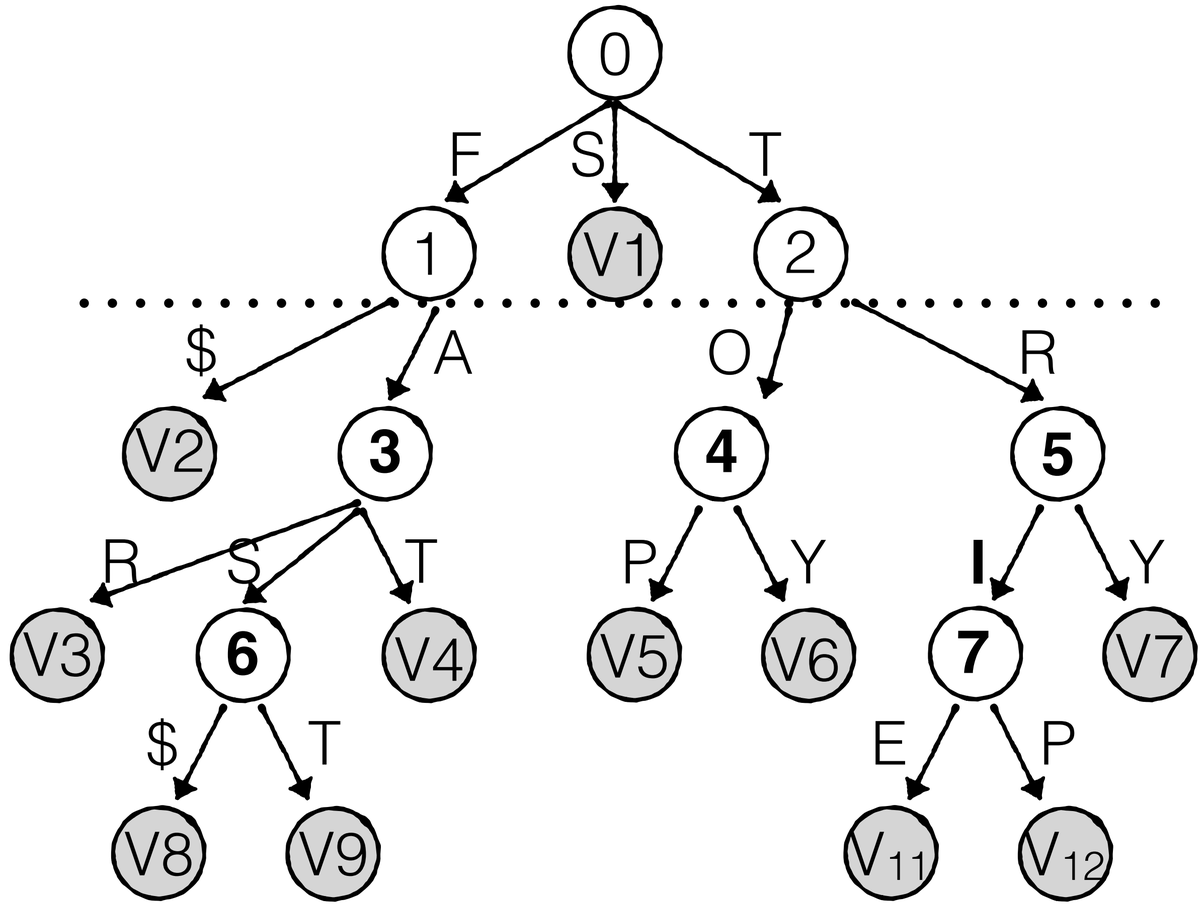


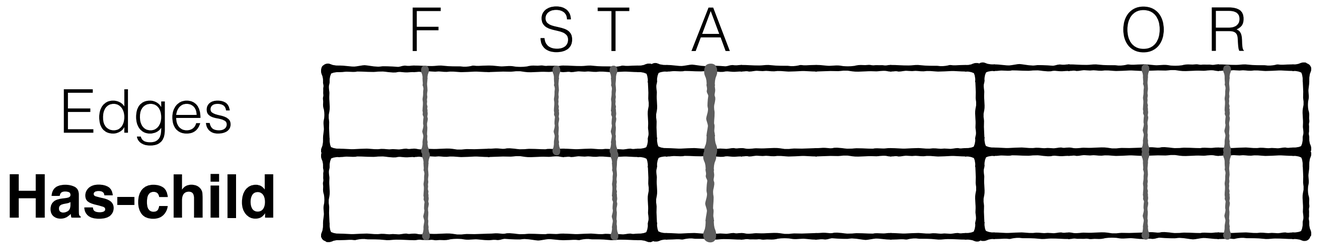


Rank(1) = 0

	R	S	T	P	Y	I	Y	$	T	E	P
Has-child	**0**	**1**	0	0	0	1	0	0	0	0	0
LOUDS	1	0	0	1	0	1	0	1	0	1	0

FA**S**

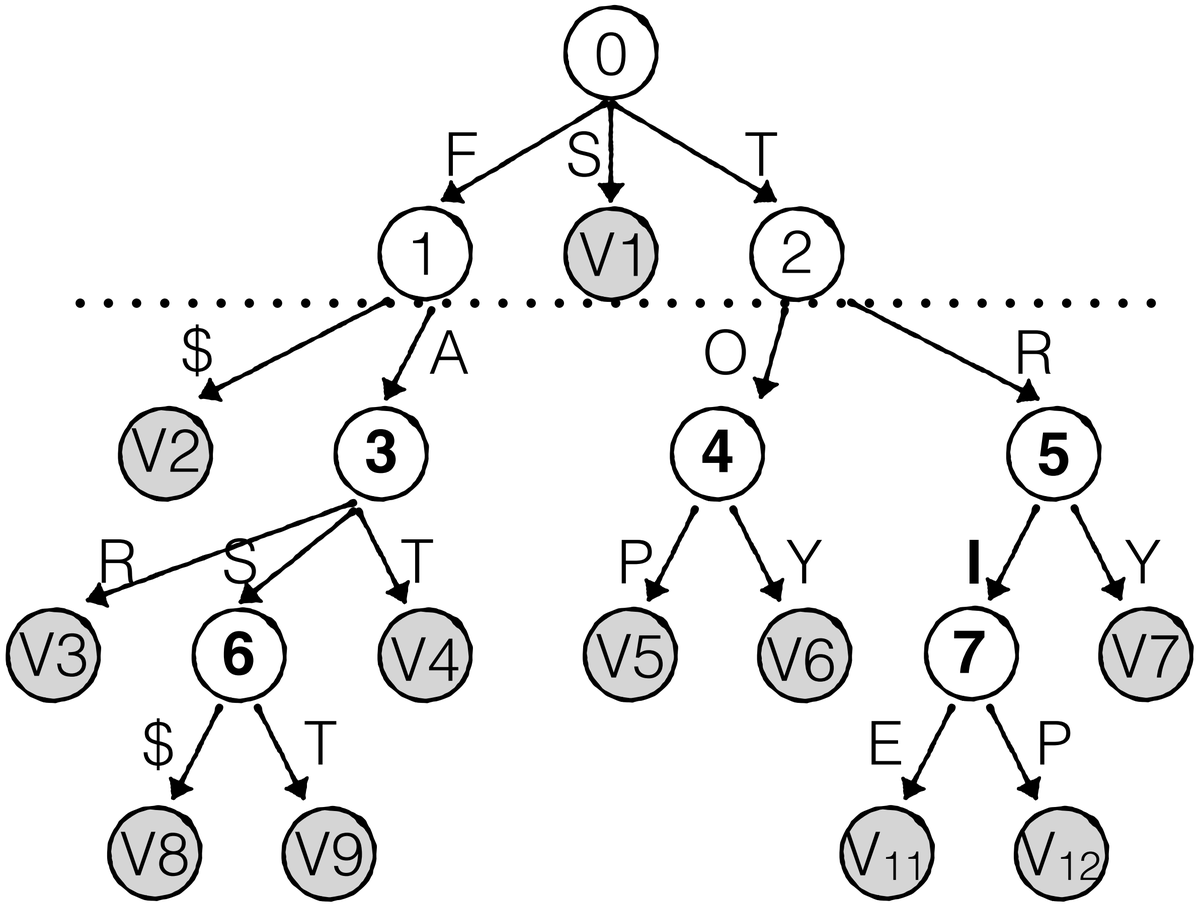


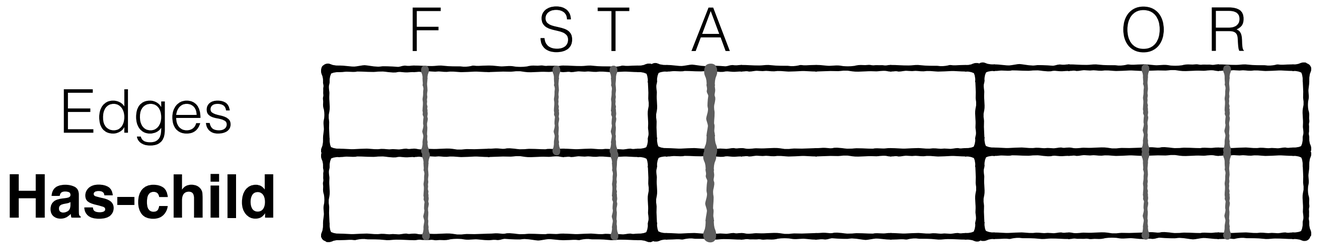


	R	**S**	T	P	Y	I	Y	$	T	E	P
Has-child	0	1	0	0	0	1	0	0	0	0	0
LOUDS	1	0	0	1	0	1	0	1	0	1	0

select(5 - 2) = 7

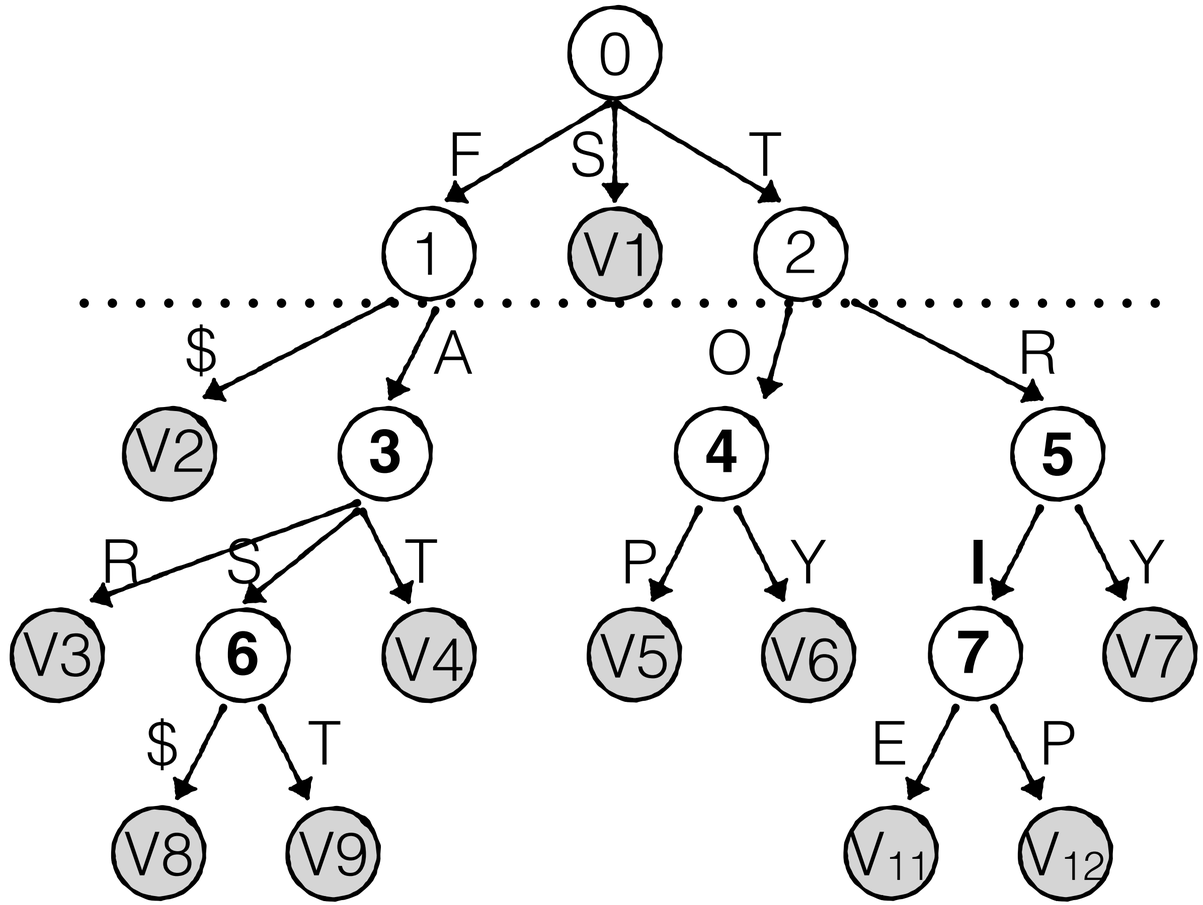
FA**S**

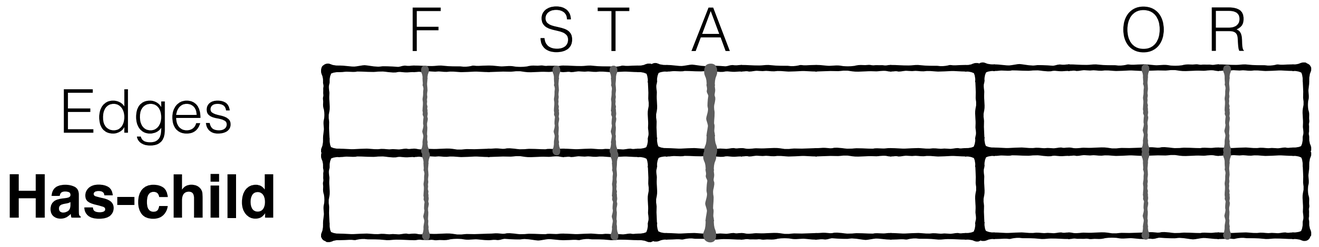




	R	S	T	P	Y	I	Y	**$**	T	E	P
Has-child	0	1	0	0	0	1	0	**0**	0	0	0
LOUDS	1	0	0	1	0	1	0	**1**	0	1	0

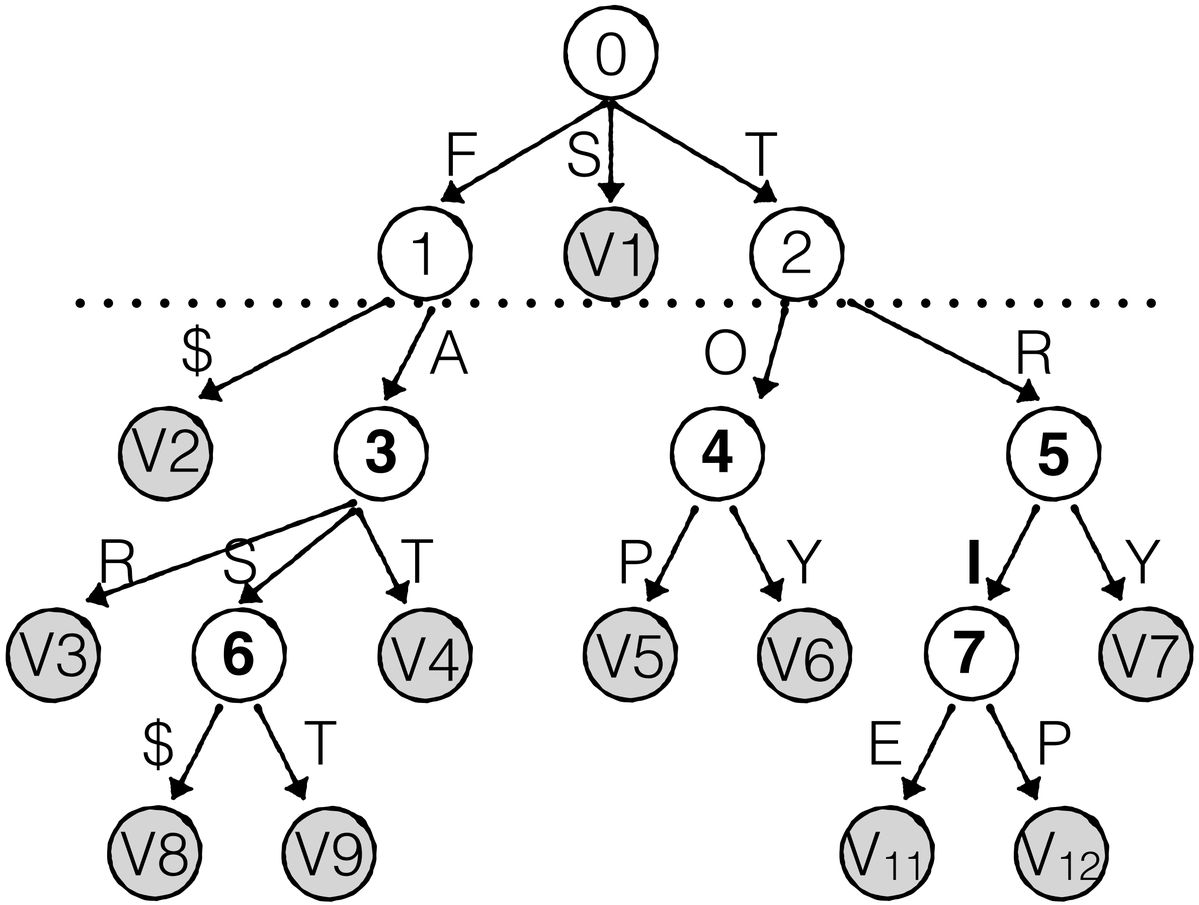
FA**S**

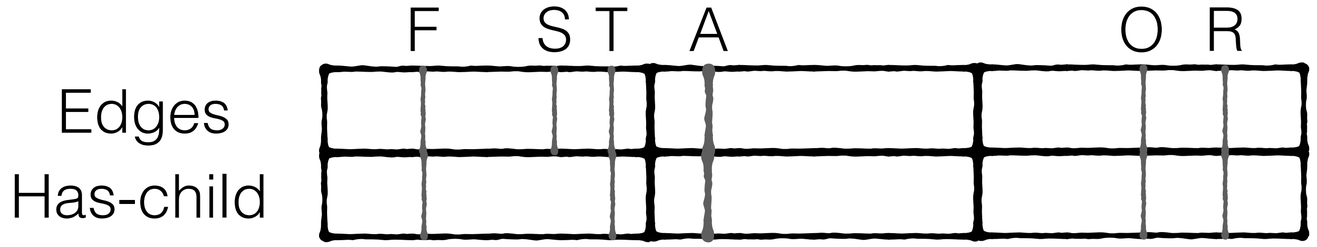




	R	S	T	P	Y	I	Y	**$**	T	E	P
Has-child	0	1	0	0	0	1	0	**0**	0	0	0
LOUDS	1	0	0	1	0	1	0	**1**	0	1	0

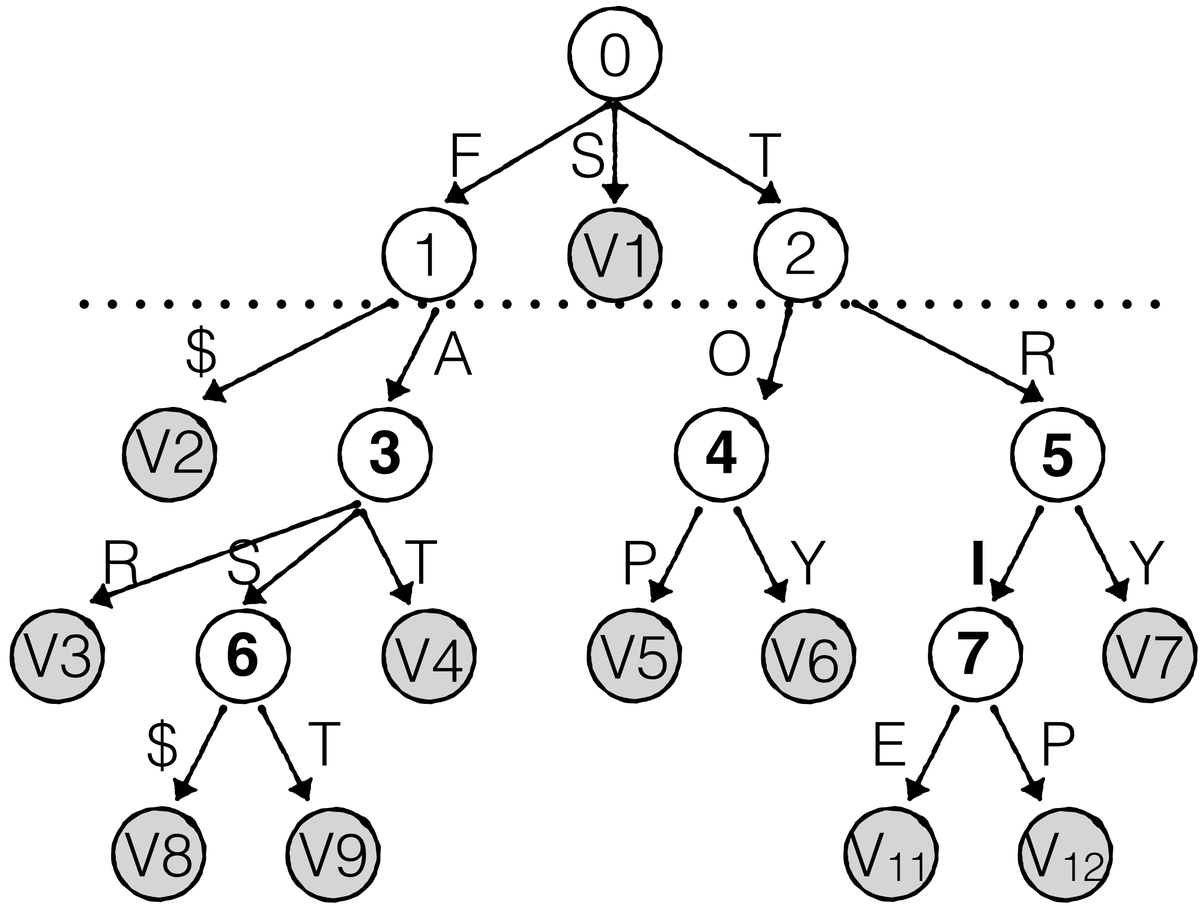
V_8

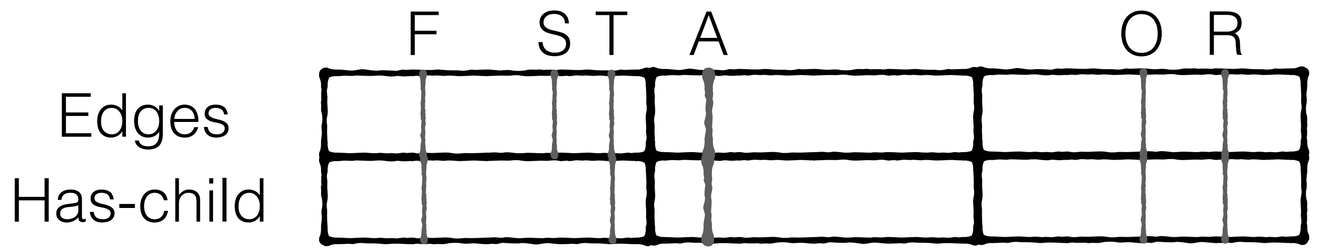




	R	S	T	P	Y	I	Y	$	T	E	P
Has-child	0	1	0	0	0	1	0	0	0	0	0
LOUDS	1	0	0	1	0	1	0	1	0	1	0

Sparse encoding is space efficient for nodes with few edges





	R	**S**	**T**	P	Y	I	Y	$	T	E	P
Has-child	0	1	0	0	0	1	0	0	0	0	0
LOUDS	1	0	0	1	0	1	0	1	0	1	0

Sparse encoding is space efficient for nodes with few edges

But slower as we must scan edges for each node

SuRF

Var-length keys & queries	**Yes**
FPR guarantee	**None**
Query speed	**O(L)** (L = key length)
Dynamic	**No**

SuRF

Memento

Diva