Bayesian Grammar Learning for Inverse Procedural Modeling

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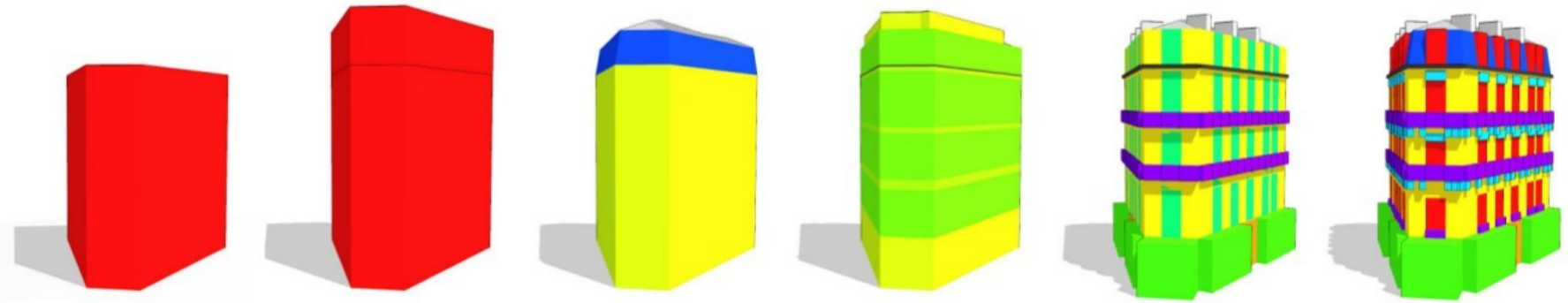
Procedural modeling



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Procedural modeling – Esri CityEngine

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Inverse procedural modeling


```
Lot      --> extrude(height) Building
Building --> comp(f) { side: Facade | top: Roof }
Facade   --> split(y) {'0.2: Groundfloor | {'0.01:
Ledge | '0.29: Floor}* }
Floor    --> split(x) {
       '0.05: Wall
     | {'0.01: Wall| '0.08: WindowTile | '0.01:
Wall}*
     | '0.05: Wall}

   ...
```

Related work

Rules are known in advance

- Metropolis Procedural Modeling (Talton et al. 2011)

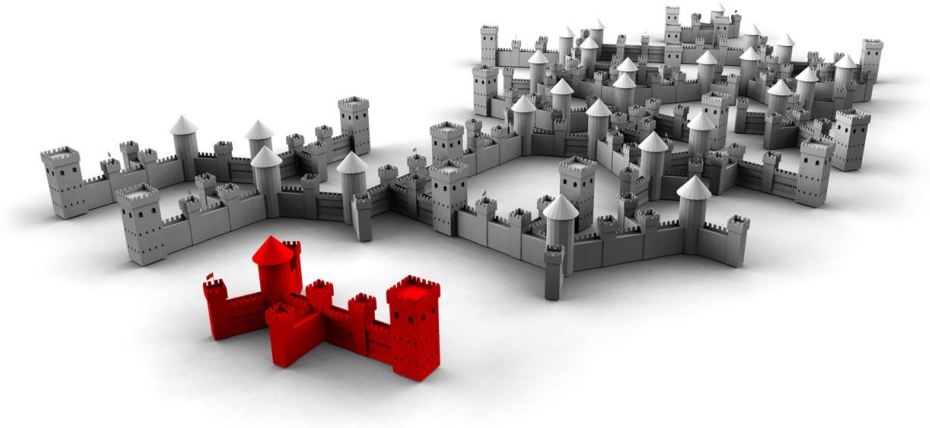
- Random Exploration of the Procedural Space for Single-View 3D Modeling of Buildings (Simon et al. 2009)

  Shape Grammar Parsing via Reinforcement Learning (Teboul et al. 2011)

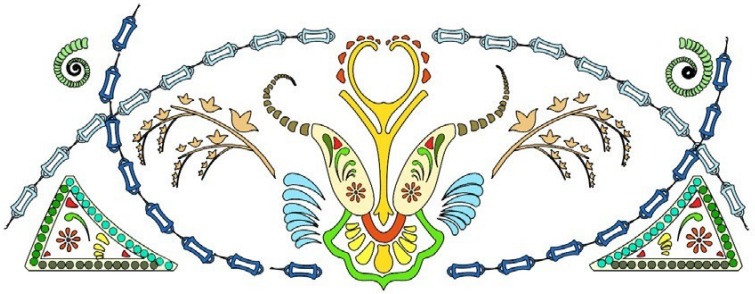
Related work

Rules are learned

- A Connection between Partial Symmetry and Inverse Procedural Modeling (Bokeloh et al. 2010)



- Inverse procedural modeling by automatic generation of L-systems (Šťava et al. 2010)



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Related work

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- Grammar learning
  - Gold, 1967: *No superfinite family of deterministic languages (including regular and context-free languages) can be identified in the limit*
  - Horning, 1969: *Stochastic* context free grammars *can* be learned from only positive examples
  - Stolcke, 1994: Introducing **Bayesian Model Merging (BMM)** for HMM, SCFG and PAG induction
  - Hwang et al, 2011: Rediscovering BMM for induction of probabilistic programs
  - Talton et al, 2012: BMM is used to learn design patterns

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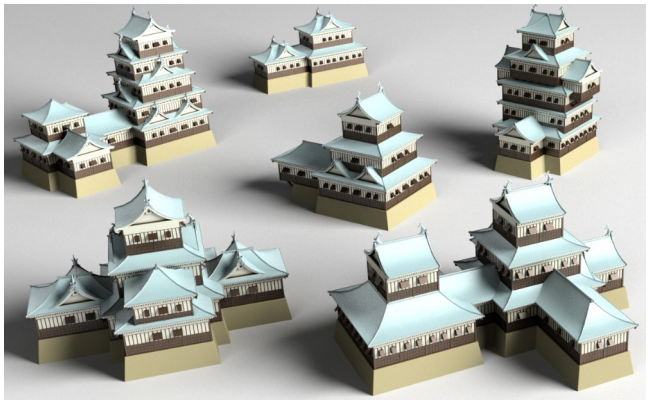

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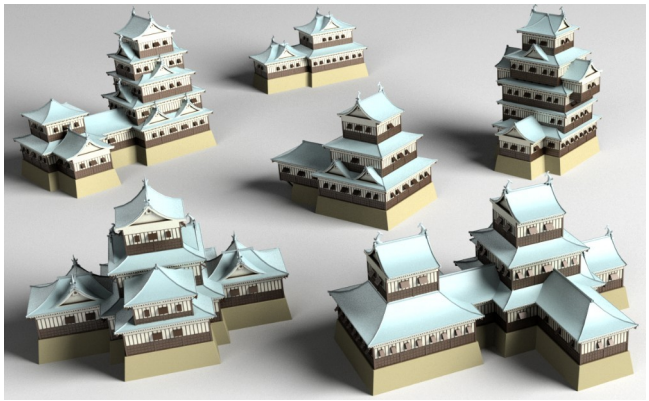
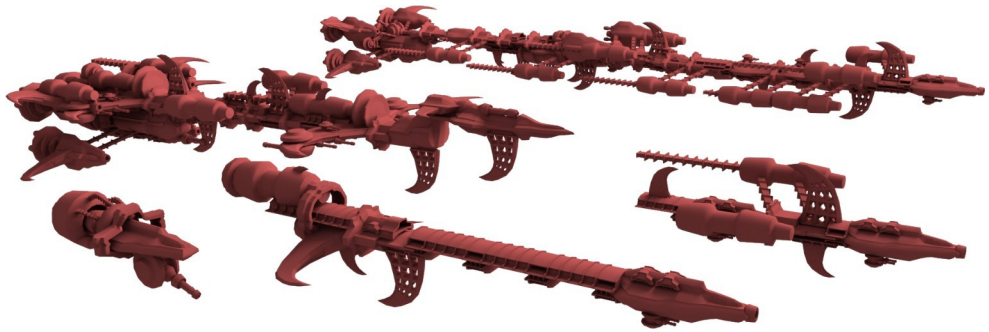
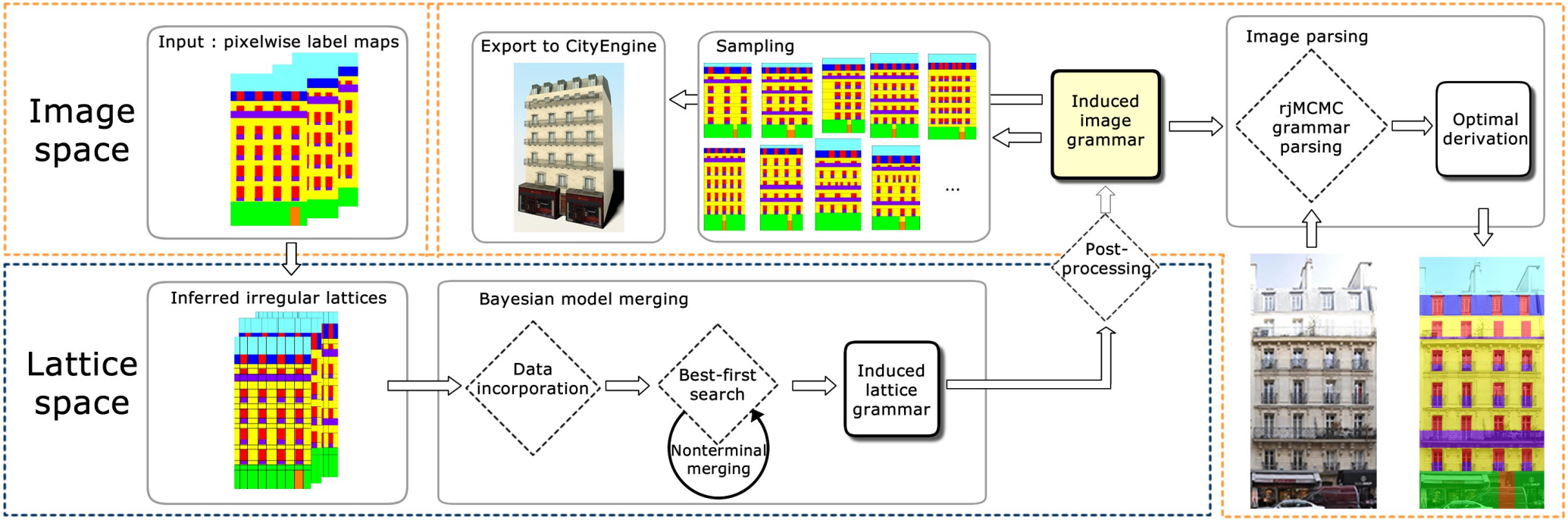


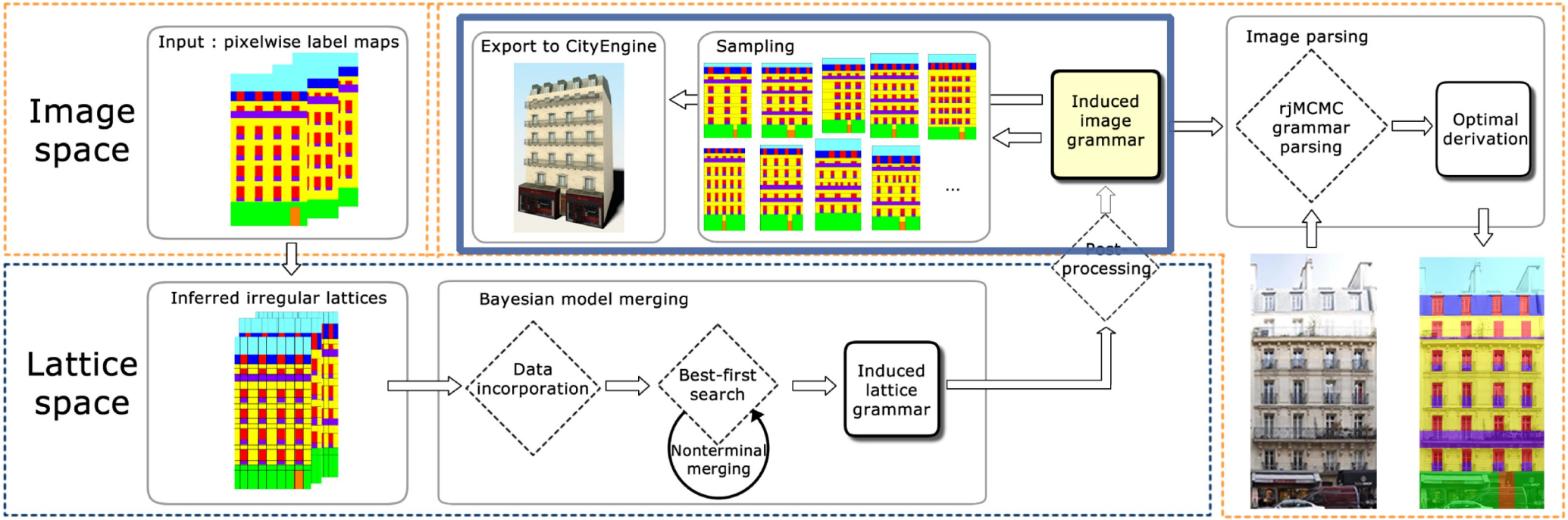


Method overview



How can we use the learned grammar?

- Sampling novel buildings



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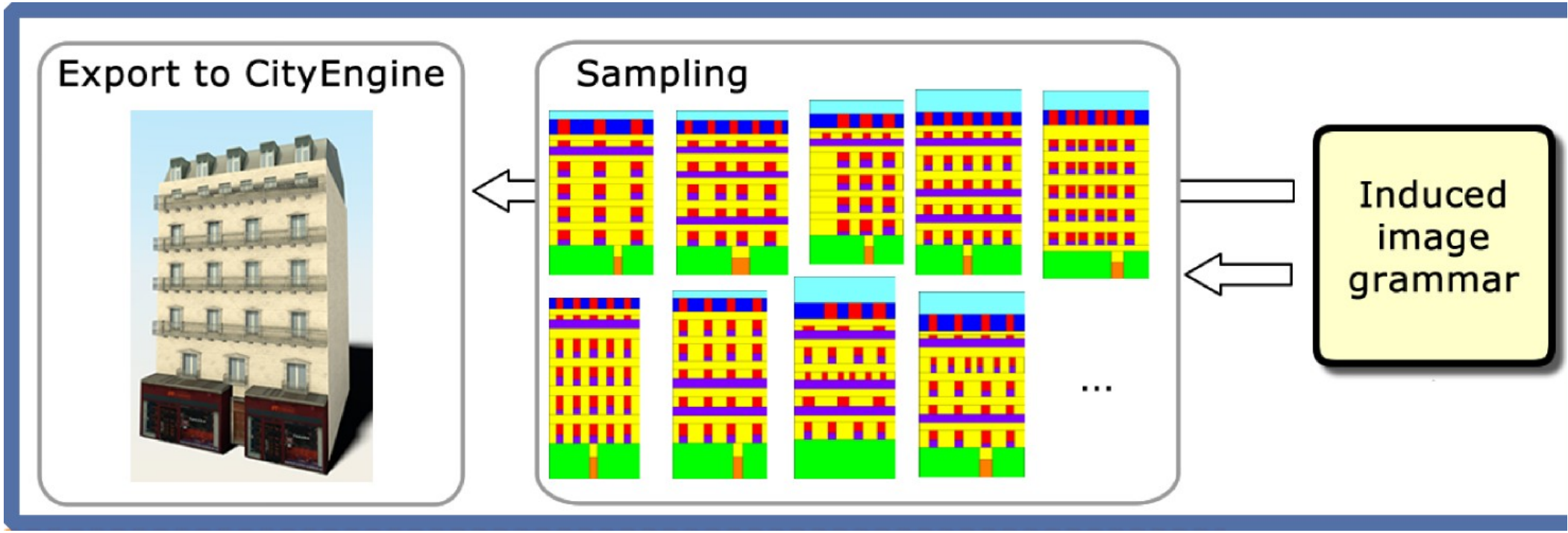

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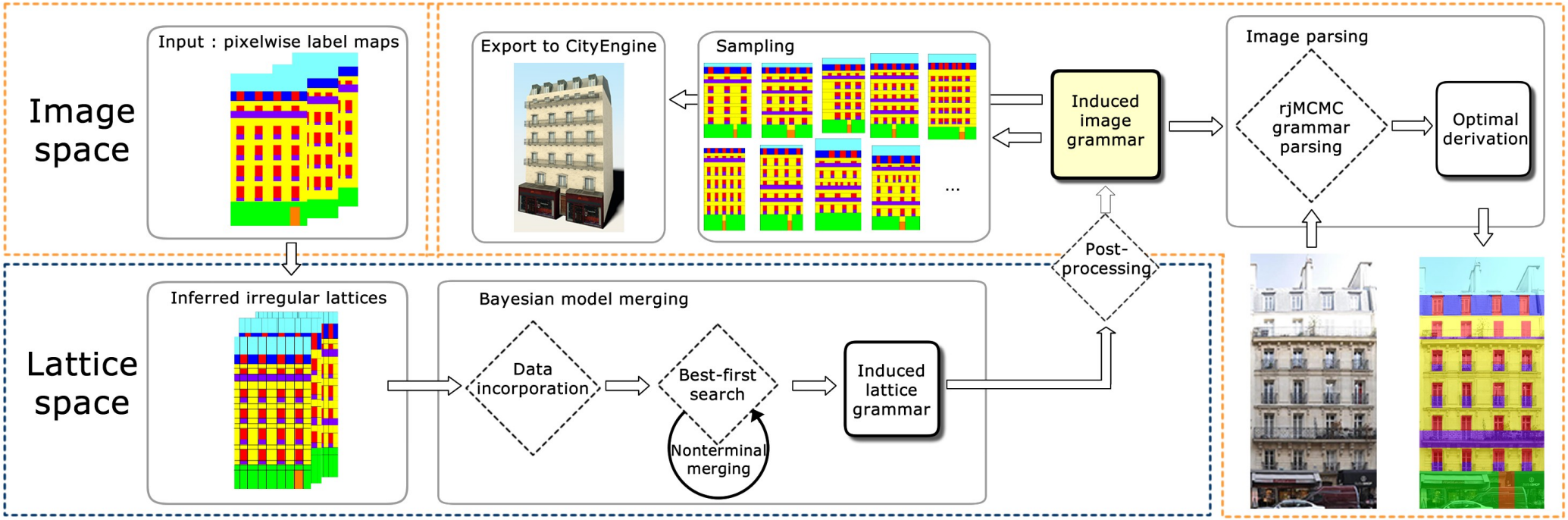

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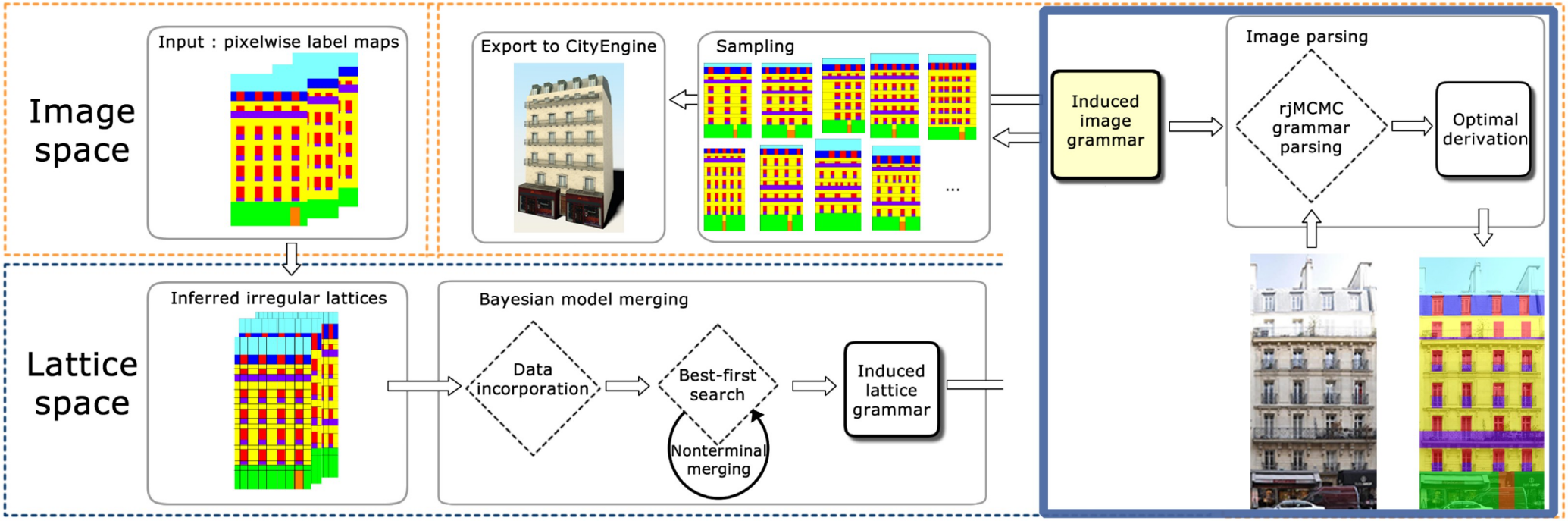

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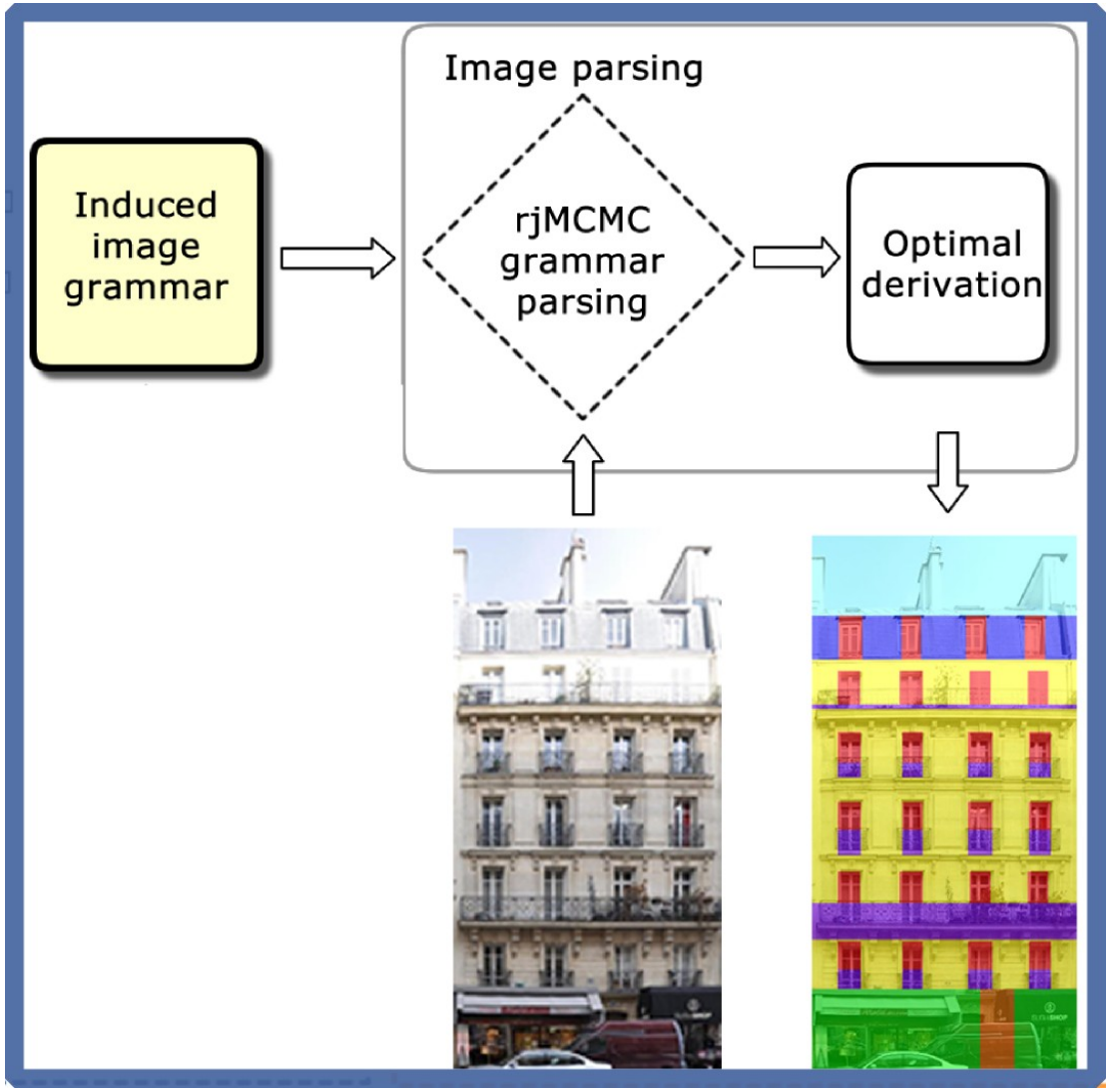

What kind of a grammar can we learn?

2D-ASCFG

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$$G = (N, T, S, R, P, A)$$

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Nonterminal symbols

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Nonterminal symbols

Terminal symbols

Axiom

What kind of a grammar can we learn?

2D-ASCFG

$$G = (N, T, S, R, P, A)$$

- N: Nonterminal symbols
- T: Terminal symbols
- S: Axiom
- R: Production rules

What kind of a grammar can we learn?

Context-Free

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What kind of a grammar can we learn?

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$$X \rightarrow \lambda_1 \lambda_2 \ldots \lambda_n$$

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Stochastic Context-Free

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Rule probabilities

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What kind of a grammar can we learn?

Attributed **S**tochastic **C**ontext-**F**ree

2D-ASCFG

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- P: Rule probabilities
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2-Dimensional **A**ttributed **S**tochastic **C**ontext-**F**ree

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Terminal symbols

Axiom

Production rules

Rule attributes

Rule probabilities

$$X \xrightarrow{H} \lambda_1\lambda_2...\lambda_n \quad [p] \qquad \{\{s_1 s_2...s_n\},...\}$$

A simple parsing example

$G = (N, T, S, R, P, A)$

N = {S, X, Y}

T = {a}

$S \xrightarrow{H} XX$	[0.2]	{ {0.5,0.5} }
$S \xrightarrow{V} XX$	[0.8]	{ {0.5,0.5} }
$X \xrightarrow{H} YY$	[0.8]	{ {0.5,0.5} }
$X \xrightarrow{V} YY$	[0.2]	{ {0.5,0.5} }
$Y \xrightarrow{H} a$	[1.0]	{ {1.0} }

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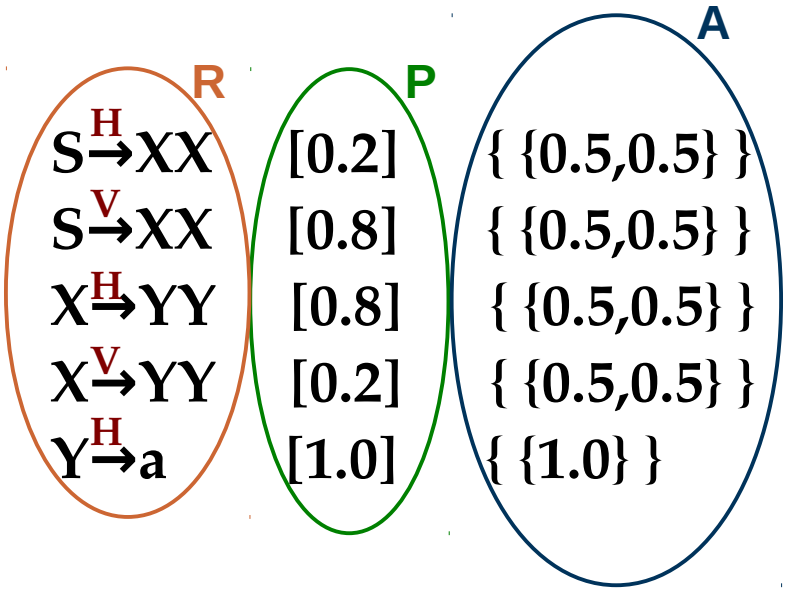

Input lattice l:

Parsing:

A simple parsing example

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Parsing:

δ_1:

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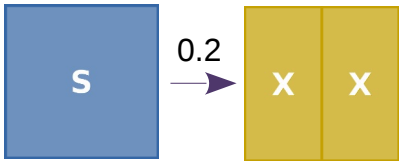

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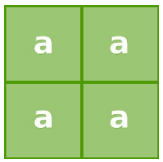

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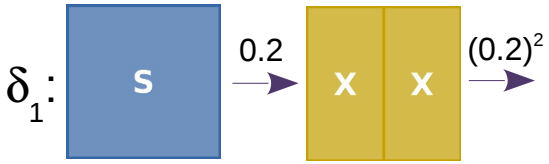

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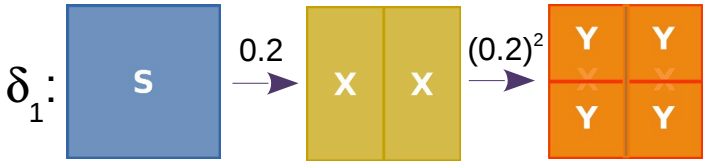

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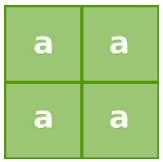


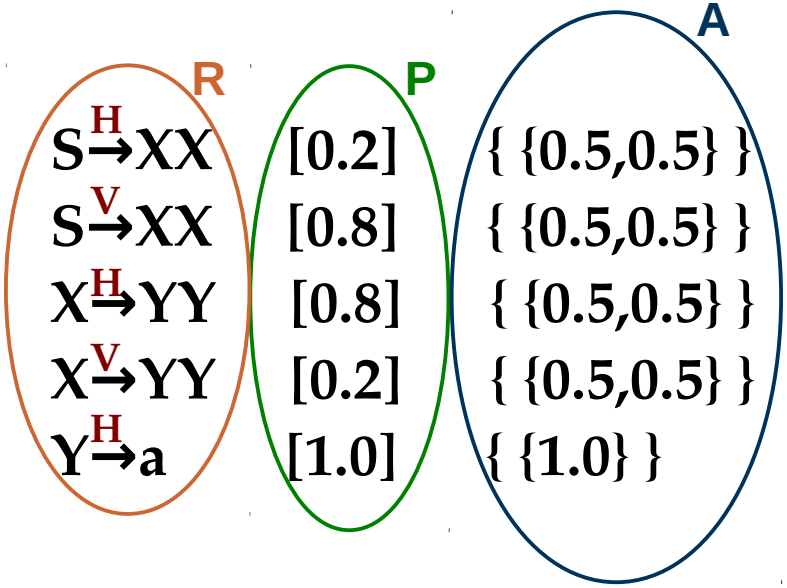
Parsing:

A simple parsing example

$G = (N, T, S, R, P, A)$

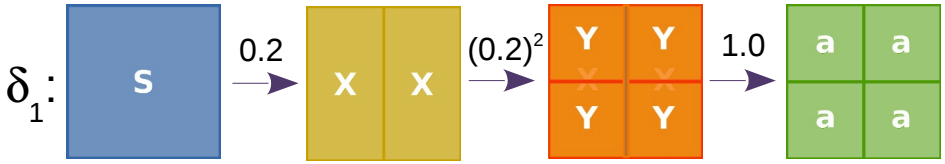
N = {S, X, Y}

T = {a}



Input lattice l:

Parsing:



A simple parsing example

$G = (N, T, S, R, P, A)$

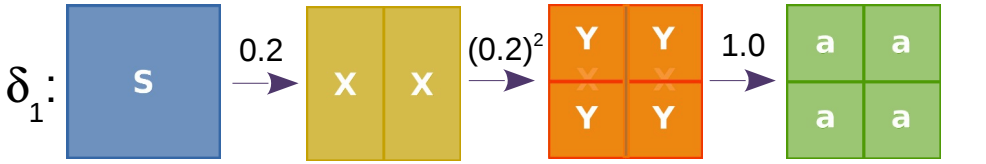
N = {S, X, Y}

T = {a}

R	P	A
$S \xrightarrow{H} XX$	[0.2]	{ {0.5,0.5} }
$S \xrightarrow{V} XX$	[0.8]	{ {0.5,0.5} }
$X \xrightarrow{H} YY$	[0.8]	{ {0.5,0.5} }
$X \xrightarrow{V} YY$	[0.2]	{ {0.5,0.5} }
$Y \xrightarrow{H} a$	[1.0]	{ {1.0} }

Input lattice l:

Parsing:



$P(\delta_1)=0.008$

A simple parsing example

$G = (N, T, S, R, P, A)$

N = {S, X, Y}

T = {a}

R	P	A
$S \xrightarrow{H} XX$	[0.2]	{ {0.5,0.5} }
$S \xrightarrow{V} XX$	[0.8]	{ {0.5,0.5} }
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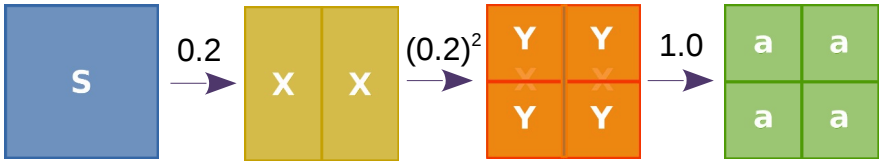
$X \xrightarrow{V} YY$	[0.2]	{ {0.5,0.5} }
$Y \xrightarrow{H} a$	[1.0]	{ {1.0} }

Input lattice l:

Parsing:

δ_1:



$P(\delta_1)=0.008$

δ_2:

A simple parsing example

$G = (N, T, S, R, P, A)$

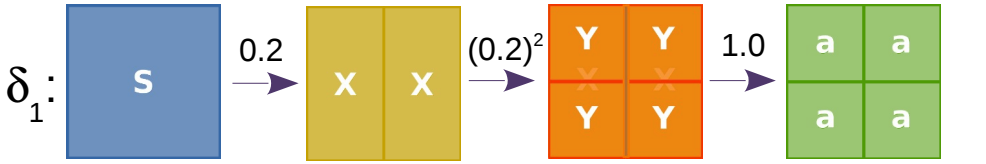
N = {S, X, Y}

T = {a}

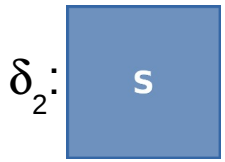
R	P	A
$S \xrightarrow{H} XX$	[0.2]	{ {0.5,0.5} }
$S \xrightarrow{V} XX$	[0.8]	{ {0.5,0.5} }
$X \xrightarrow{H} YY$	[0.8]	{ {0.5,0.5} }
$X \xrightarrow{V} YY$	[0.2]	{ {0.5,0.5} }
$Y \xrightarrow{H} a$	[1.0]	{ {1.0} }

Input lattice l:

Parsing:



$P(\delta_1)=0.008$



A simple parsing example

$G = (N, T, S, R, P, A)$

N = {S, X, Y}

T = {a}

R	P	A
$S \xrightarrow{H} XX$	[0.2]	{ {0.5,0.5} }
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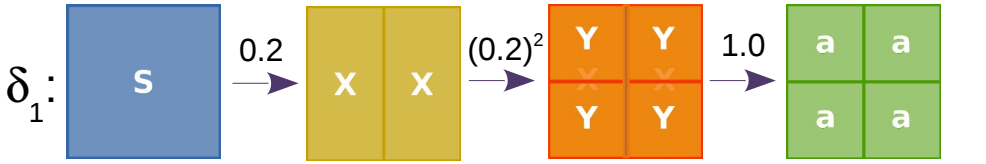
Input lattice l:

Parsing:



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T = {a}

R	P	A
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$X \xrightarrow{H} YY$	[0.8]	{ {0.5,0.5} }
$X \xrightarrow{V} YY$	[0.2]	{ {0.5,0.5} }
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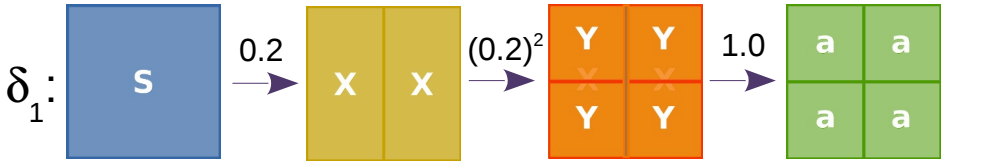
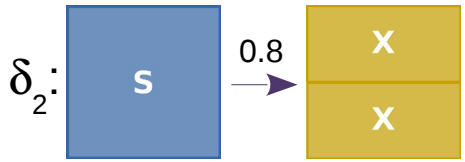
Input lattice l:

Parsing:



$P(\delta_1)=0.008$



A simple parsing example

$G = (N, T, S, R, P, A)$

N = {S, X, Y}

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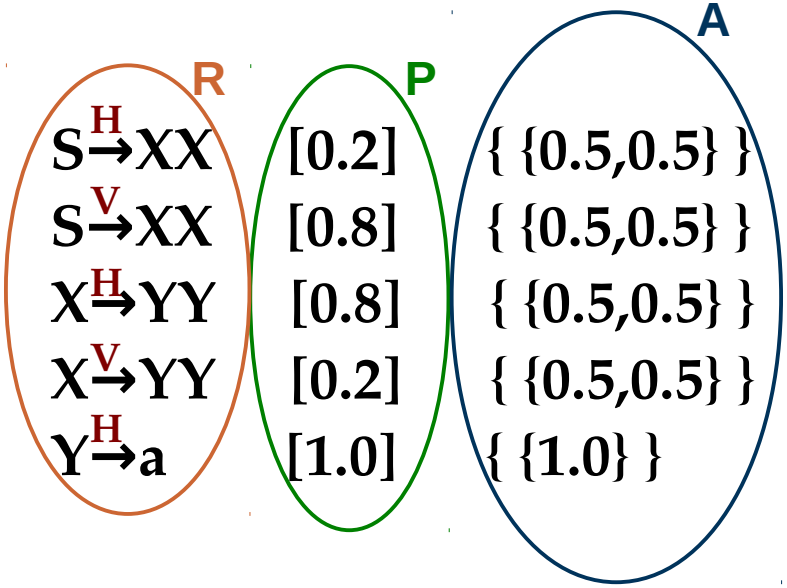
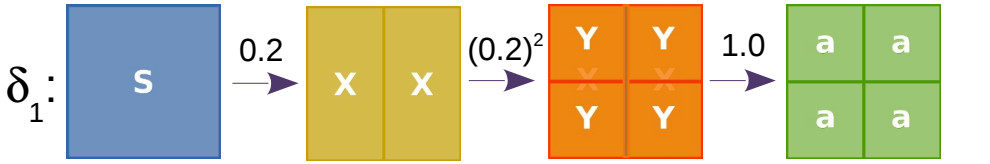
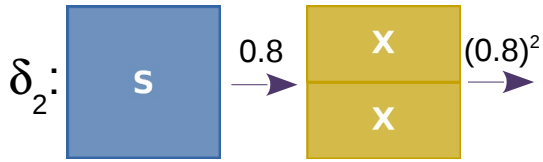


Input lattice l:

Parsing:



$P(\delta_1)=0.008$

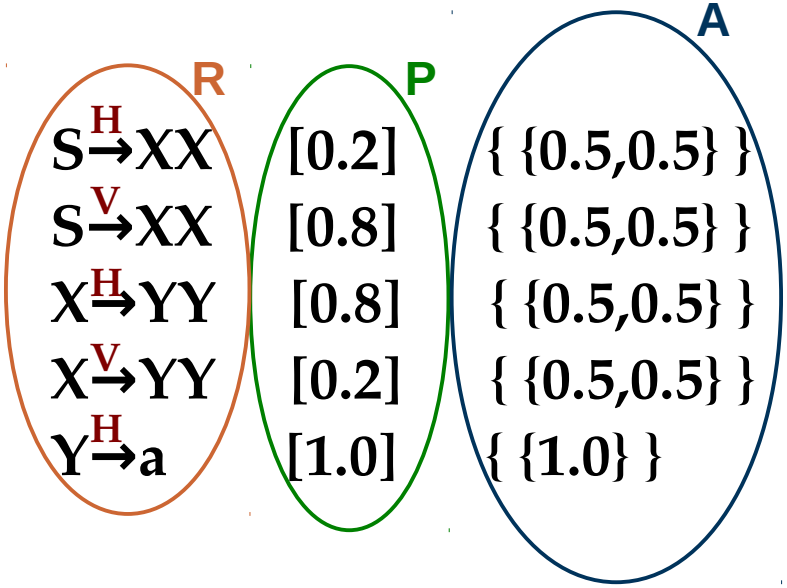


A simple parsing example

$G = (N, T, S, R, P, A)$

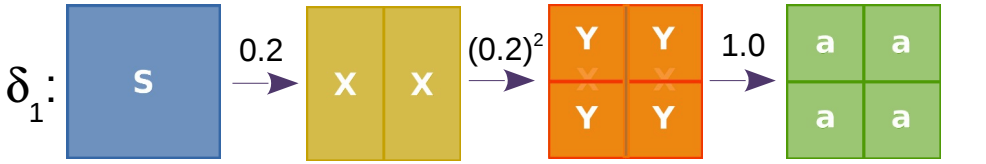
N = {S, X, Y}

T = {a}



Input lattice l:

Parsing:



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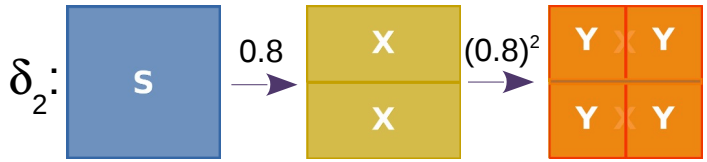

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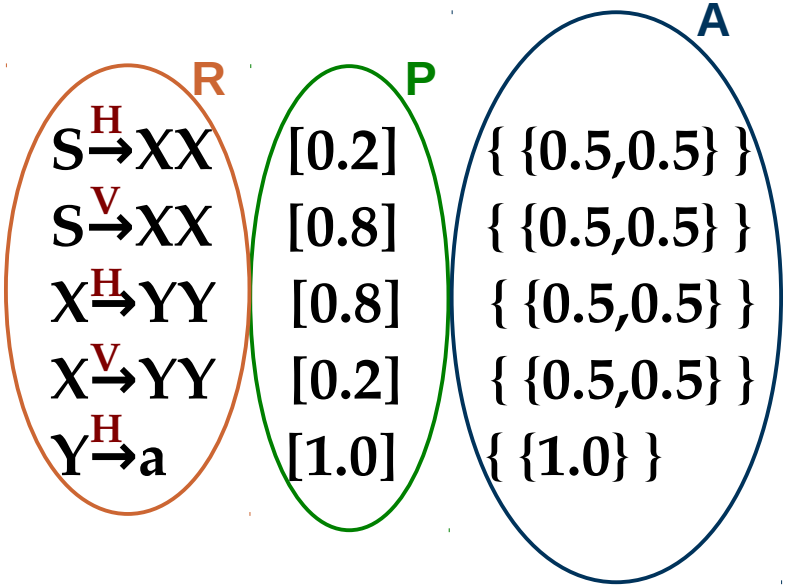
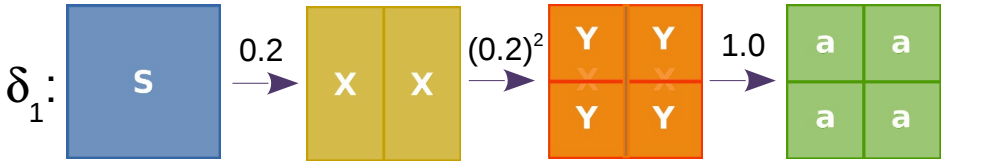


Input lattice l:

Parsing:



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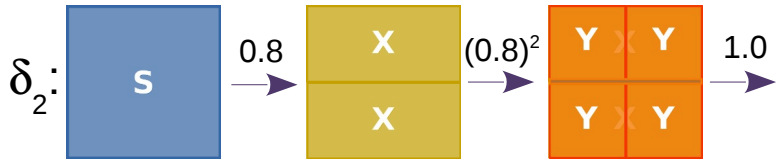

A simple parsing example

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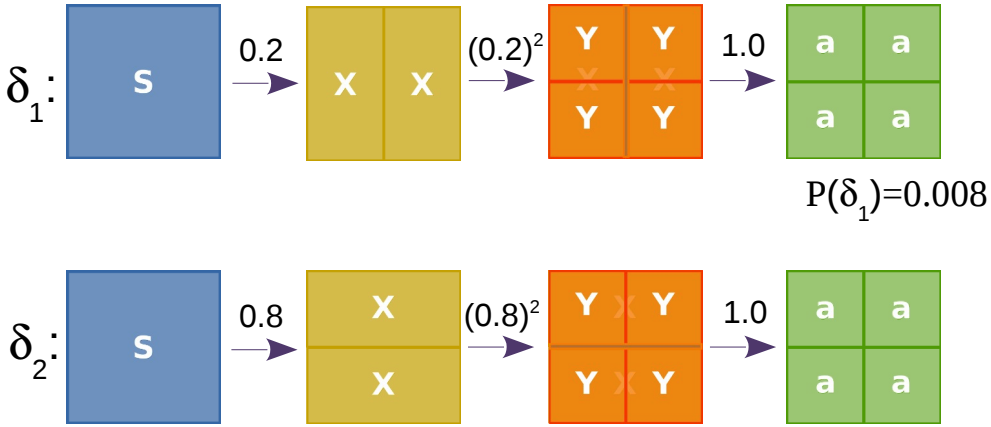
T = {a}

R	P	A
$S \xrightarrow{H} XX$	[0.2]	{ {0.5,0.5} }
$S \xrightarrow{V} XX$	[0.8]	{ {0.5,0.5} }
$X \xrightarrow{H} YY$	[0.8]	{ {0.5,0.5} }
$X \xrightarrow{V} YY$	[0.2]	{ {0.5,0.5} }
$Y \xrightarrow{H} a$	[1.0]	{ {1.0} }

Input lattice l:

Parsing:

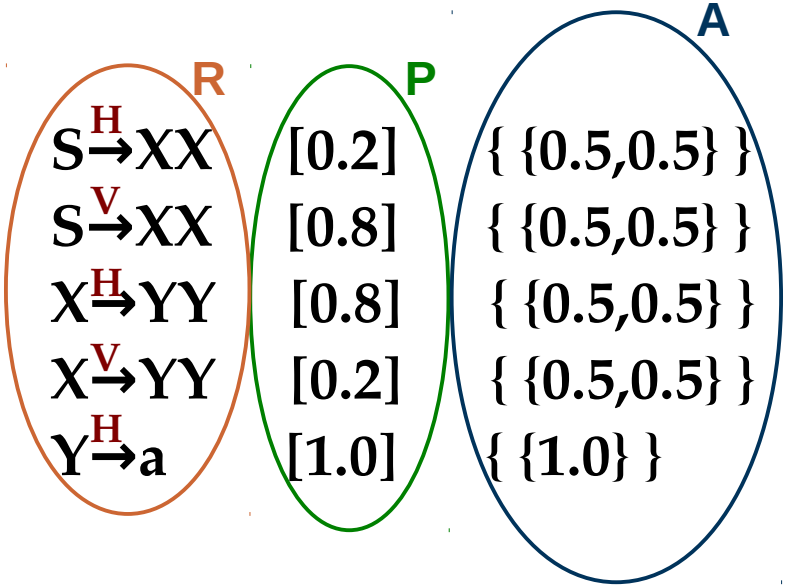


A simple parsing example

$G = (N, T, S, R, P, A)$

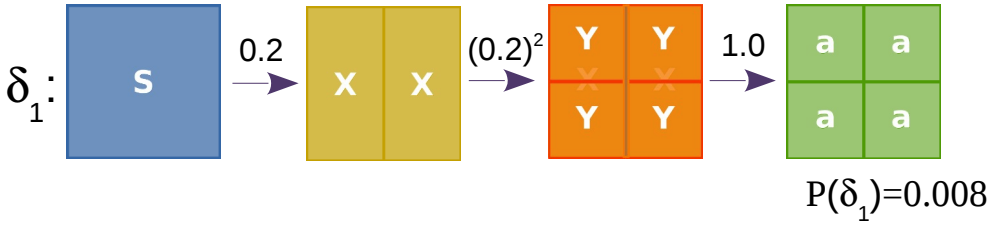
N = {S, X, Y}

T = {a}

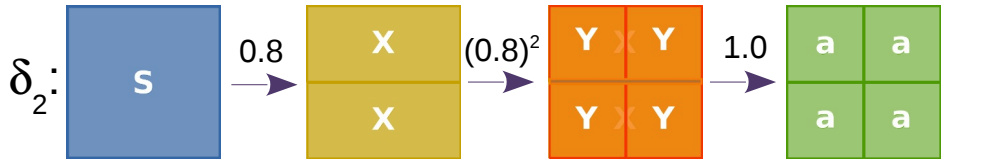


Input lattice l:

Parsing:



$P(\delta_1)=0.008$



$P(\delta_2)=0.512$

A simple parsing example

$G = (N, T, S, R, P, A)$

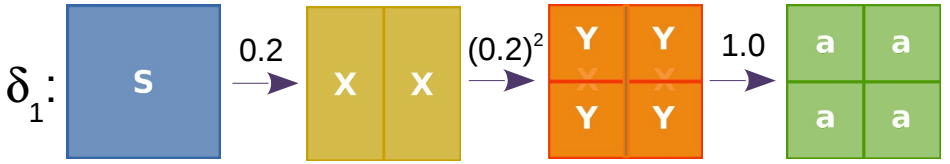
N = {S, X, Y}

T = {a}

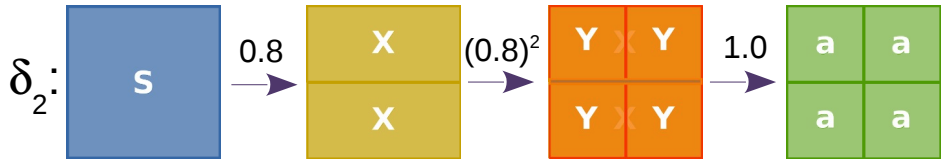
R	P	A
$S \xrightarrow{H} XX$	[0.2]	{ {0.5,0.5} }
$S \xrightarrow{V} XX$	[0.8]	{ {0.5,0.5} }
$X \xrightarrow{H} YY$	[0.8]	{ {0.5,0.5} }
$X \xrightarrow{V} YY$	[0.2]	{ {0.5,0.5} }
$Y \xrightarrow{H} a$	[1.0]	{ {1.0} }

Input lattice l:

Parsing:



$P(\delta_1)=0.008$



$P(\delta_2)=0.512$

Input likelihood: $L(l \mid G) = \sum_{\delta \Rightarrow l} P(\delta) = 0.52$

A simple parsing example

$G = (N, T, S, R, P, A)$

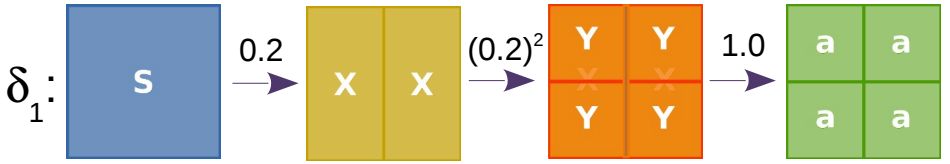
N = {S, X, Y}

T = {a}

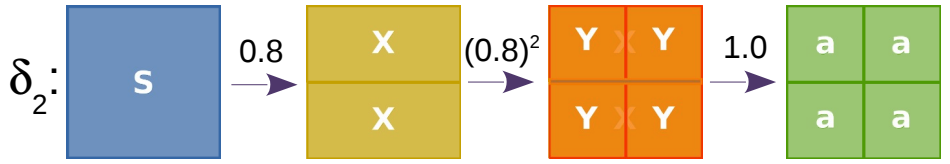
R	P	A
$S \xrightarrow{H} XX$	[0.2]	{ {0.5,0.5} }
$S \xrightarrow{V} XX$	[0.8]	{ {0.5,0.5} }
$X \xrightarrow{H} YY$	[0.8]	{ {0.5,0.5} }
$X \xrightarrow{V} YY$	[0.2]	{ {0.5,0.5} }
$Y \xrightarrow{H} a$	[1.0]	{ {1.0} }

Input lattice l:

Parsing:



$P(\delta_1)=0.008$

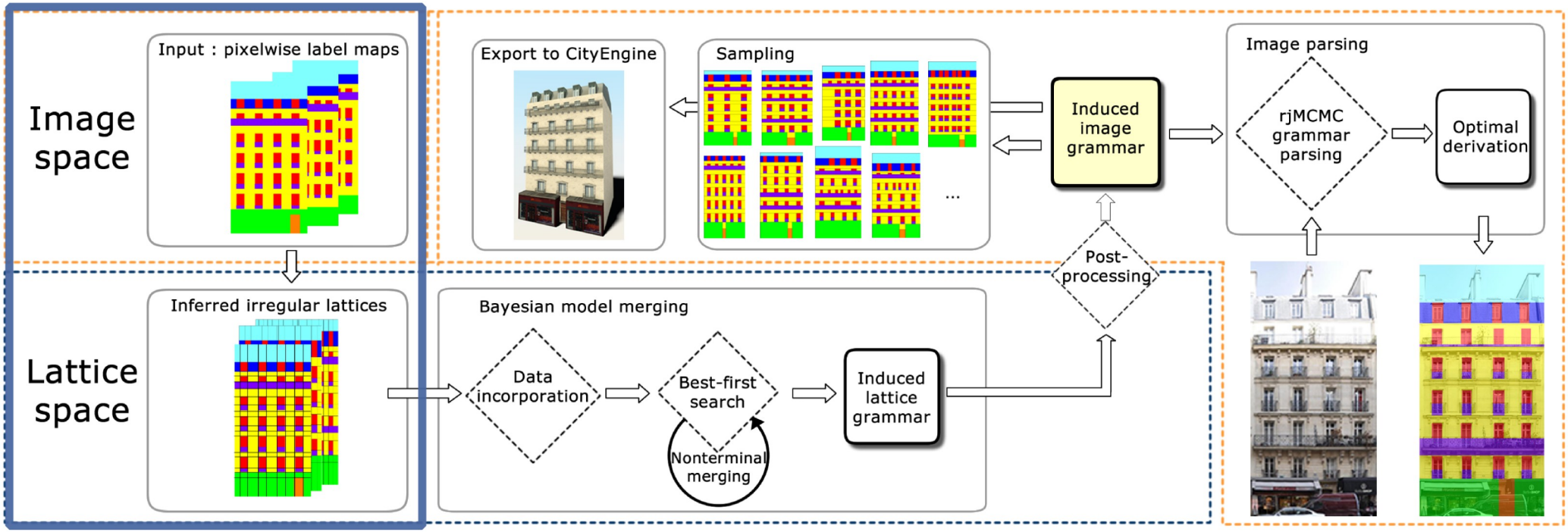


$P(\delta_2)=0.512$

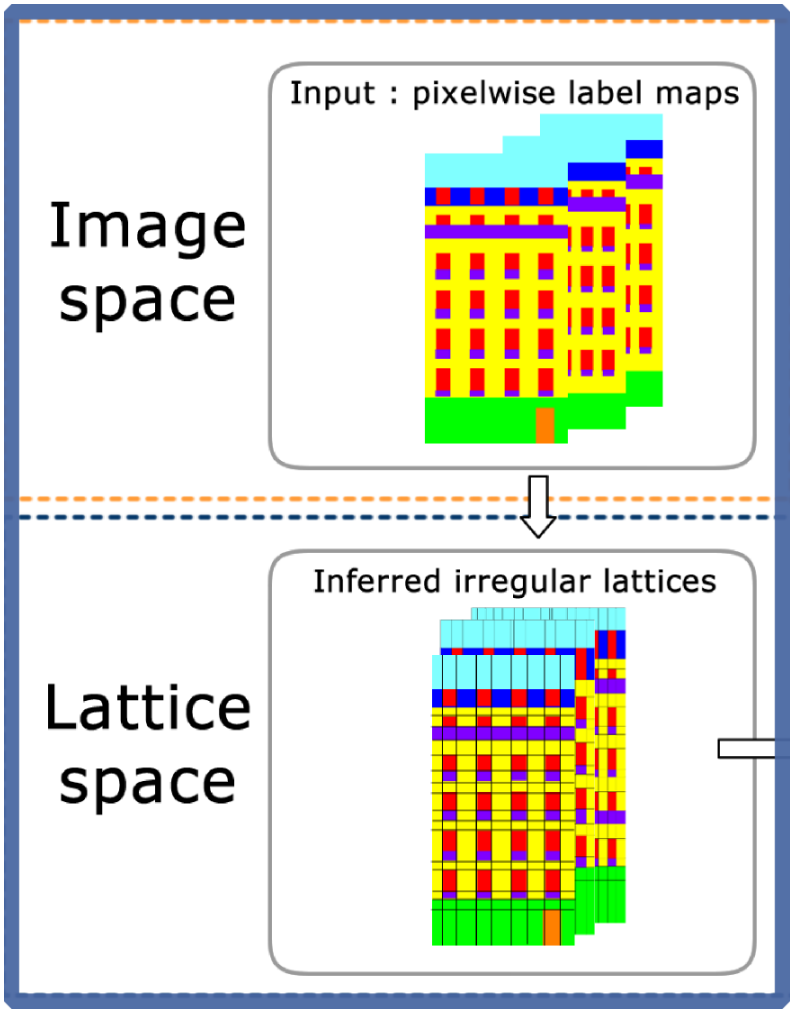
Input likelihood: $L(l \mid G) = \sum_{\delta \Rightarrow l} P(\delta) = 0.52$

Viterbi approximation: $L(l \mid G) = \max_{\delta \Rightarrow l} P(\delta) = 0.512$

Method overview

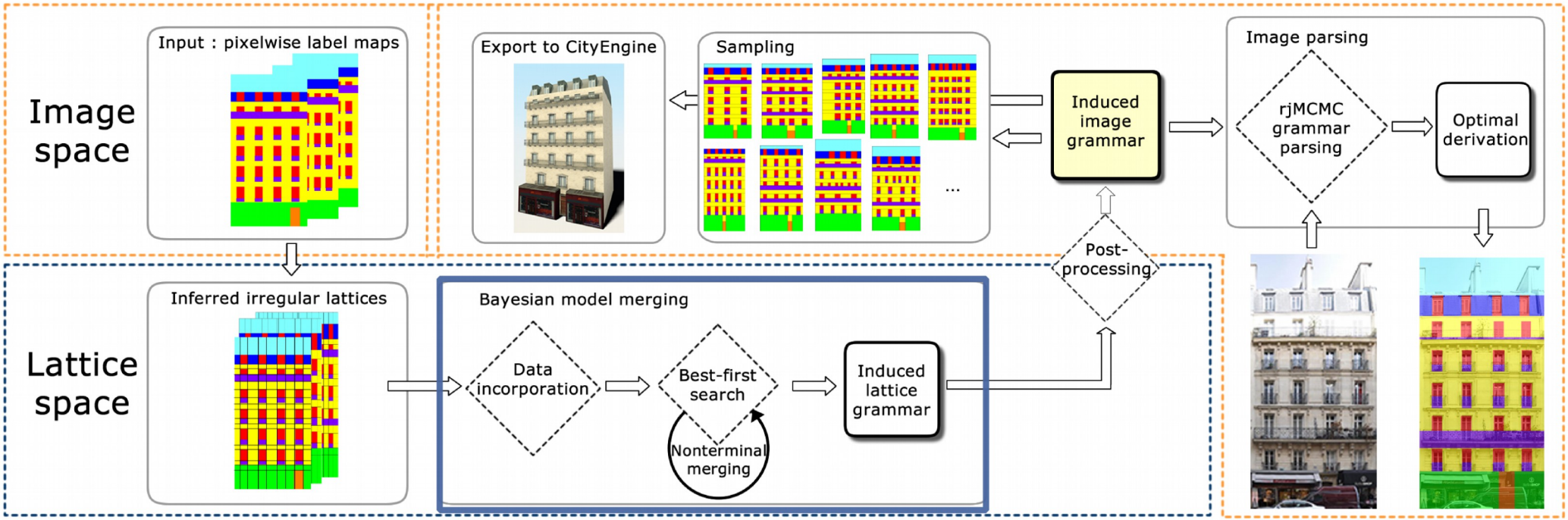


Lattice creation



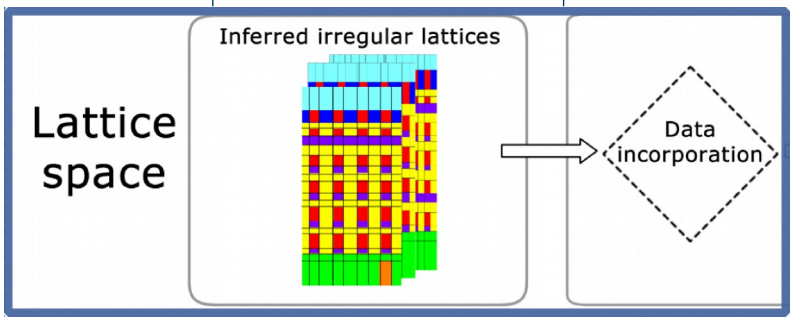
- Approach similar to Riemenschneider et al. (2012)
- Every rectangular region (tile) is labeled with the majority vote from the corresponding pixel labels

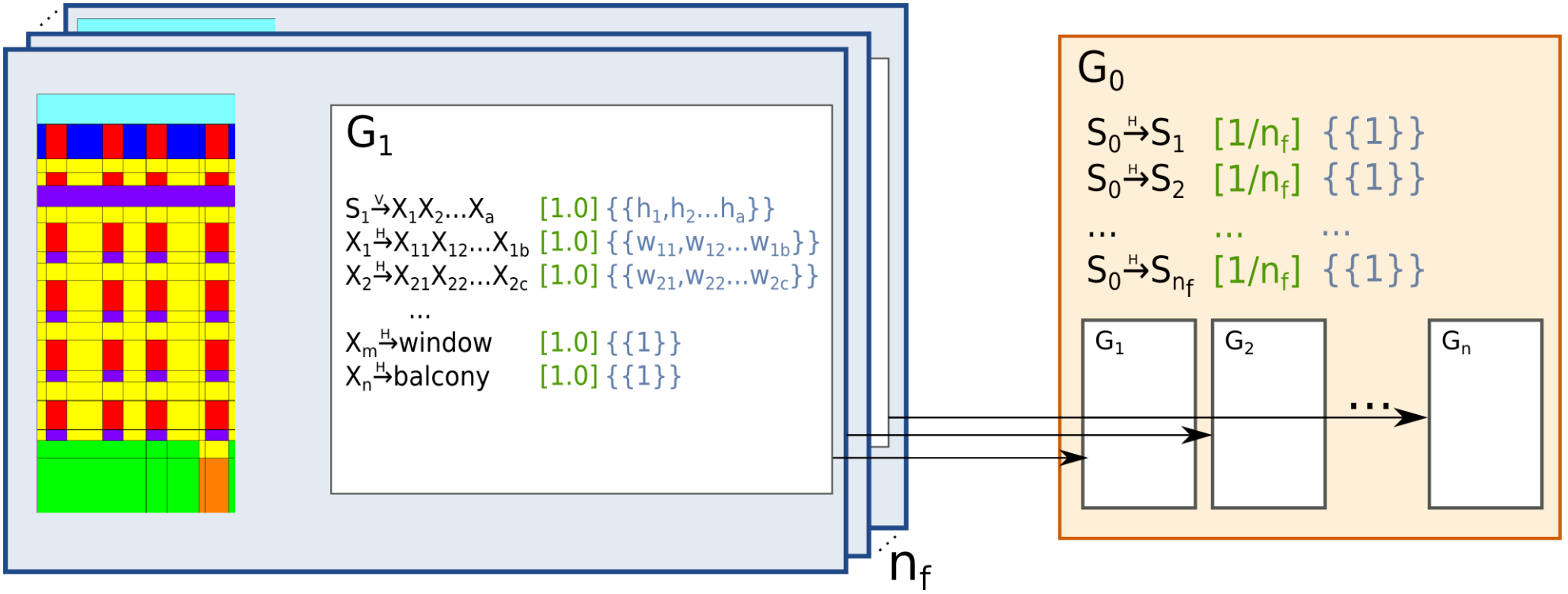
Bayesian model merging



- **Data incorporation**: given a body of data, build an initial grammar which generates only the input examples.
- **Model merging**: propose a candidate grammar by altering the structure of the currently best grammar.
- **Model evaluation**: evaluate the fitness of the candidate grammar compared to the currently best grammar.
- **Search**: use model merging to explore the grammar space, searching for the optimal grammar

Data incorporation





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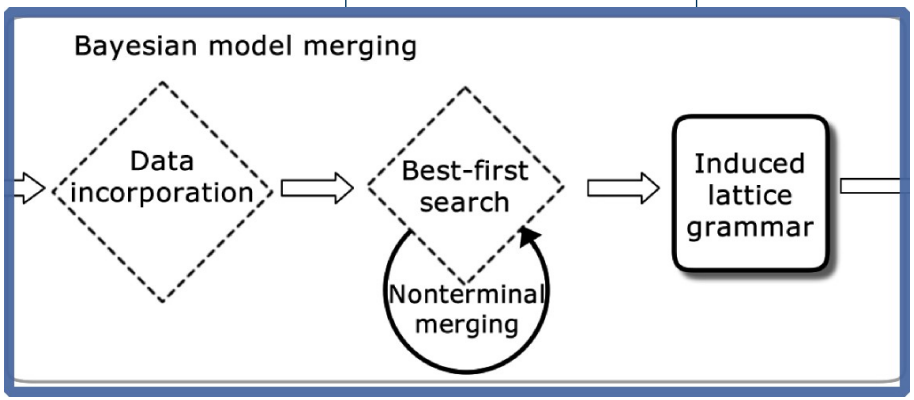
Nonterminal merging: Proposing candidate grammars



- Two nonterminals X_1 and X_2 are selected from the current grammar and replaced with a new nonterminal Y
  - RHS occurrences are replaced:

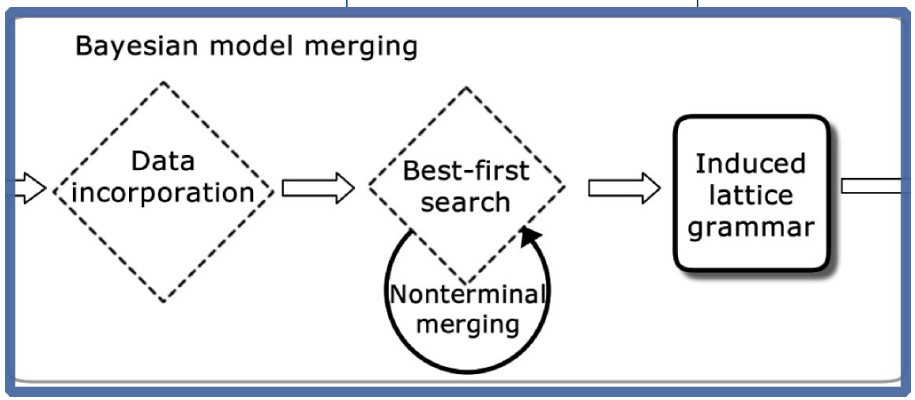
$$\begin{matrix} Z_1 \rightarrow \mu_1 X_1 \lambda_1 \\ Z_2 \rightarrow \mu_2 X_2 \lambda_2 \end{matrix} \xrightarrow{\text{merge}} \begin{matrix} Z_1 \rightarrow \mu_1 Y \lambda_1 \\ Z_2 \rightarrow \mu_2 Y \lambda_2 \end{matrix}$$

  - If $Z_1=Z_2$, $\mu_1=\mu_2$, $\lambda_1=\lambda_2$, productions are merged and their attribute sets joined
  - LHS occurrences are also replaced:

$$\begin{matrix} X_1 \rightarrow \lambda_1 \\ X_2 \rightarrow \lambda_2 \end{matrix} \xrightarrow{\text{merge}} \begin{matrix} Y \rightarrow \lambda_1 \\ Y \rightarrow \lambda_2 \end{matrix}$$

  - Productions of the form $Y \rightarrow Y$ are removed
  - Restriction: X_1 and X_2 must be 'label-compatible'

Evaluating candidate grammars

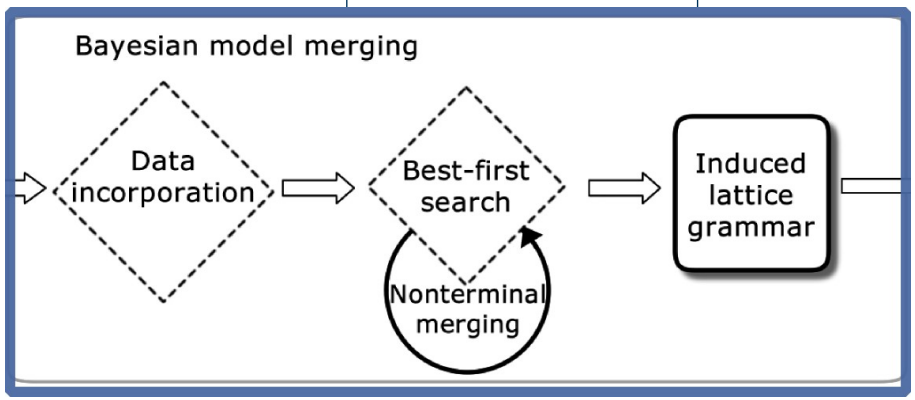


- Goal: find the best trade-off between fit to the input data D and a general preference for simpler models (MDL)

- From a Bayesian perspective:

$$\textit{maximize}\ \ P(G \mid D) \sim P(G) \cdot P(D \mid G)$$

posterior prior likelihood



Evaluating candidate grammars

Prior term

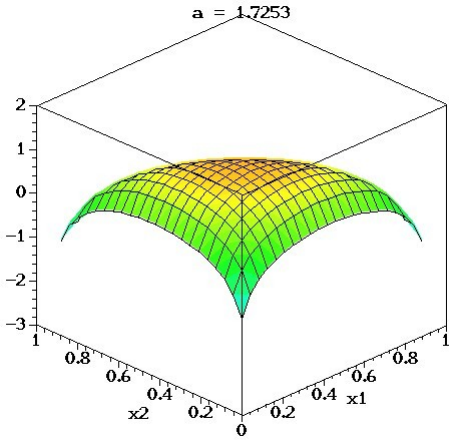
$$P(G)=P(G_s)\cdot P(\theta_g \mid G_s)$$

Structure prior Parameter prior

- Structure prior follows the Minimum Description Length (MDL) principle
  - $P(G_s) = e^{-DL(G_s)}$
  - Grammar description length (in bits):

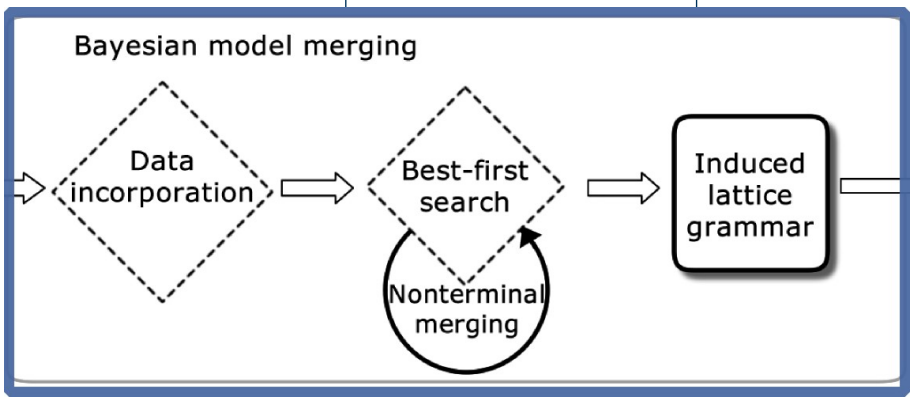
$$DL(G_s)=\Sigma_{r\in R}\ \Sigma_{n\in(r\cap N)}\log|N|$$

- Parameter prior is a symmetrical Dirichlet

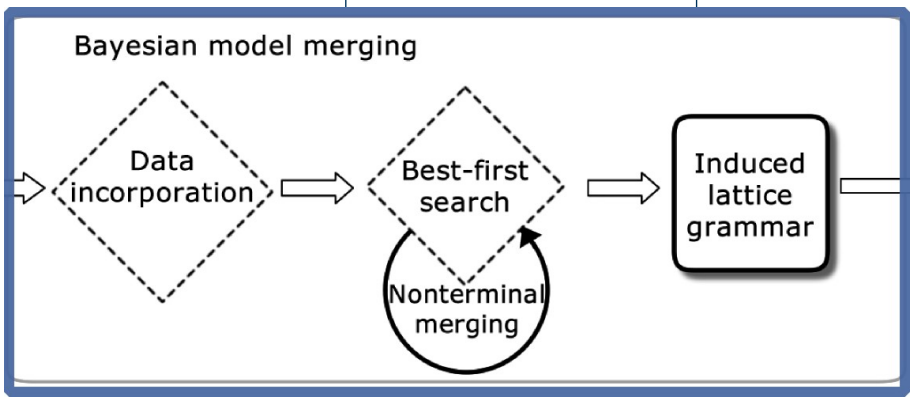


Evaluating candidate grammars

Likelihood term



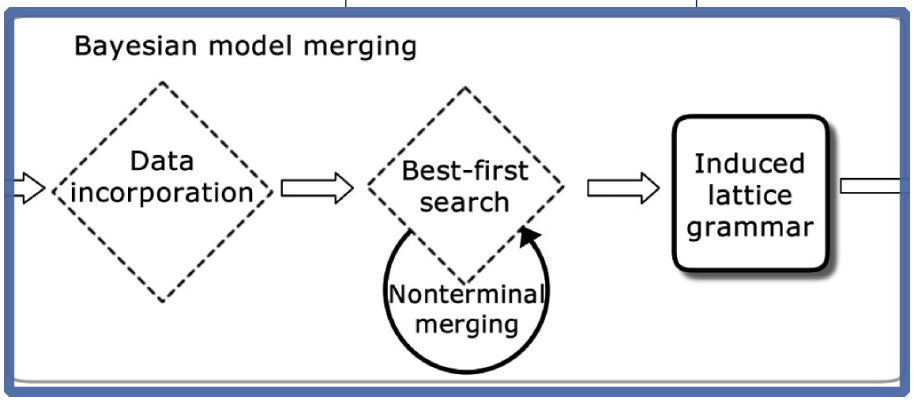
Evaluating candidate grammars



Likelihood term

- To calculate the likelihood, one must integrate over the parameter prior...

- ...or, use the Viterbi assumption:
  - Every input sample is generated by a **single** derivation tree of the grammar
  - The likelihood of that sample is then the product of all rule probabilities used in the Viterbi derivation
  - However, both the Viterbi derivations and the optimal values of rule probabilities θ_g are unknown!



Evaluating candidate grammars

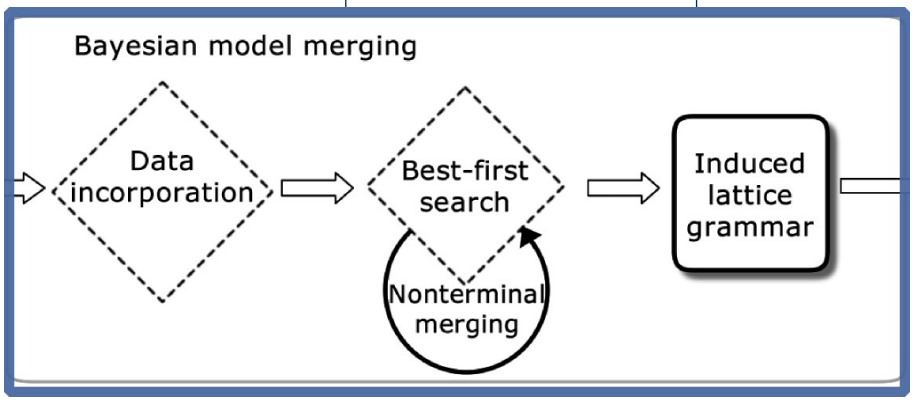
Likelihood term

- To calculate the likelihood, one must integrate over the parameter prior...

$$P(D|G_s) = \int_{\theta_g} P(\theta_g|G_s)P(D|G_s,\theta_g)d\theta_g$$

- ...or, use the Viterbi assumption:
  - Every input sample is generated by a **single** derivation tree of the grammar
  - The likelihood of that sample is then the product of all rule probabilities used in the Viterbi derivation
  - However, both the Viterbi derivations and the optimal values of rule probabilities θ_g are unknown!

Evaluating candidate grammars

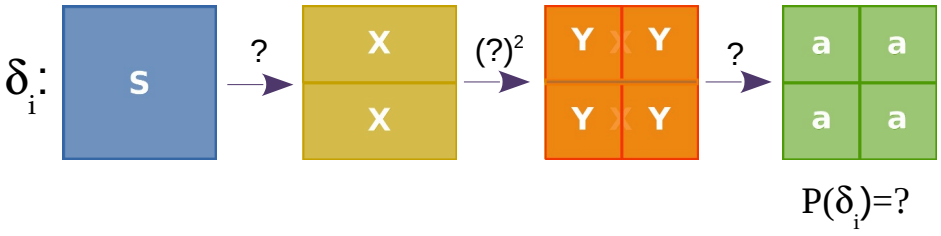


Likelihood term

- To calculate the likelihood, one must integrate over the parameter prior...

$$P(D|G_s) = \int_{\theta_g} P(\theta_g|G_s)P(D|G_s,\theta_g)d\theta_g$$

- ...or, use the Viterbi assumption:
  - Every input sample is generated by a **single** derivation tree of the grammar
  - The likelihood of that sample is then the product of all rule probabilities used in the Viterbi derivation
  - However, both the Viterbi derivations and the optimal values of rule probabilities θ_g are unknown!



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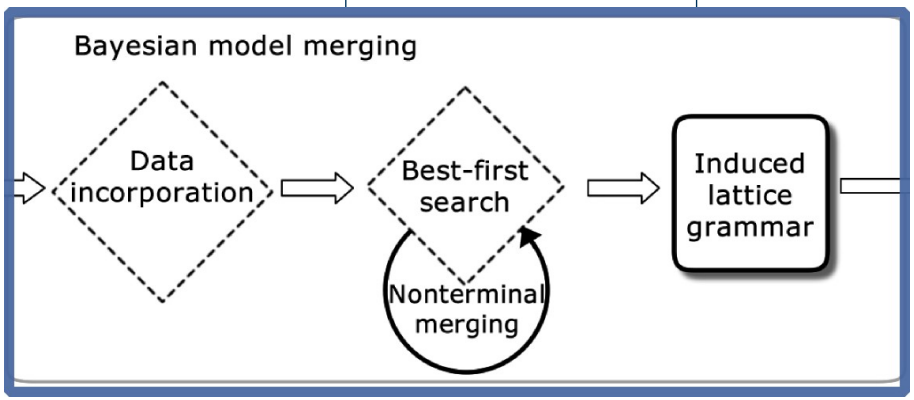

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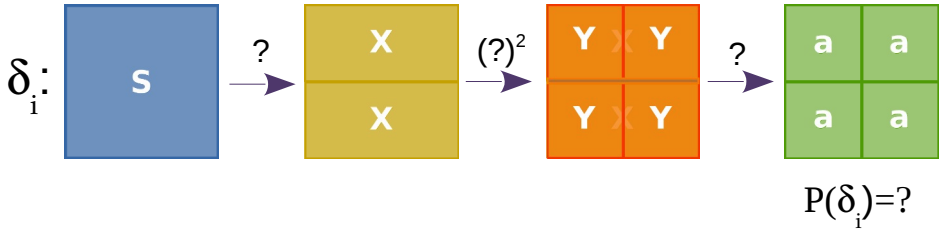

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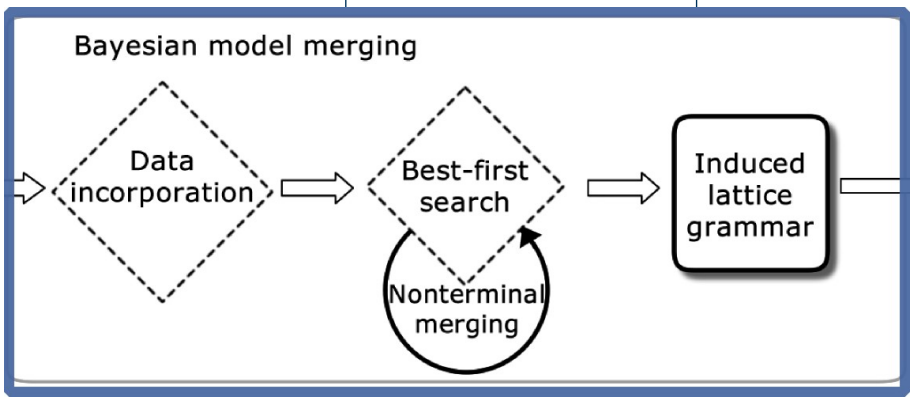

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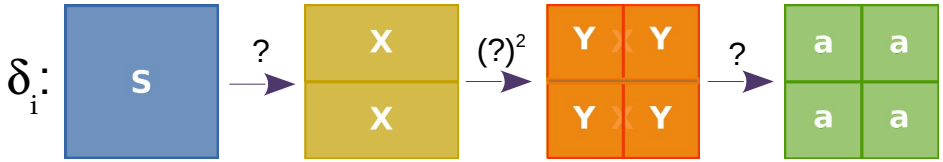

- Solution: Expectation-Maximization
- **E-step**: starting from an estimate of θ_g, calculate the expected usage counts of each rule
  - Find Viterbi derivations of all input data, count the number of times each rule is used
- **M-step: r**e-estimate the rule probabilities θ_g:

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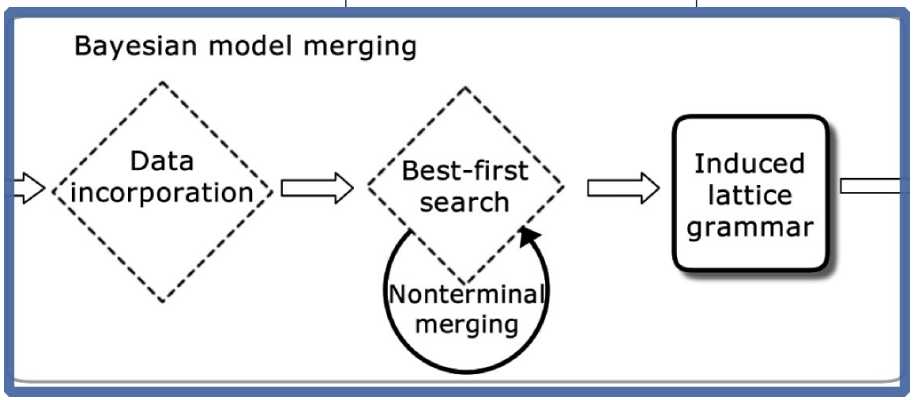

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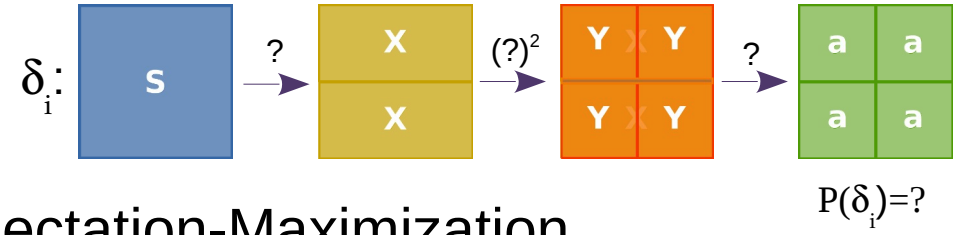

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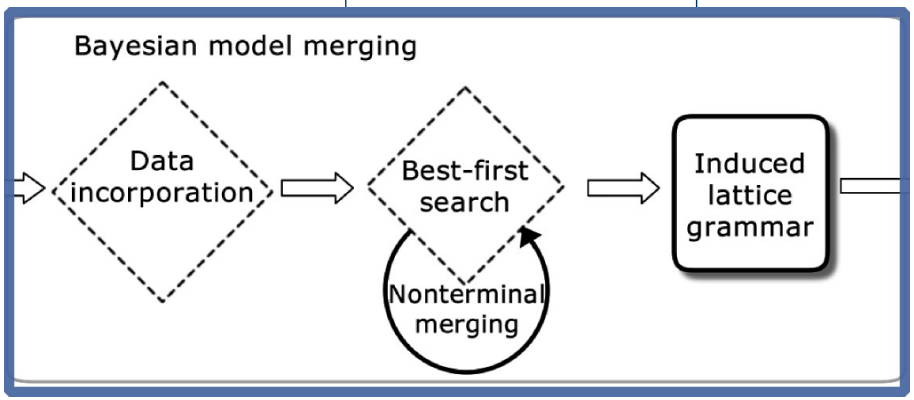

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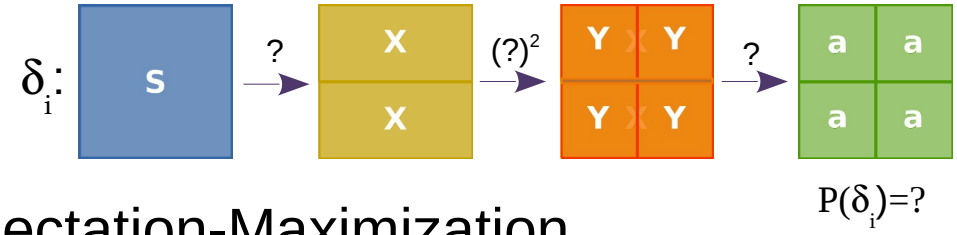

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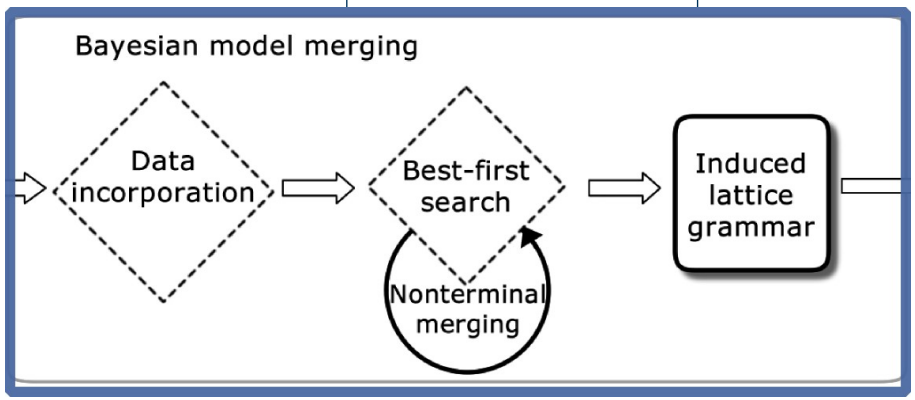

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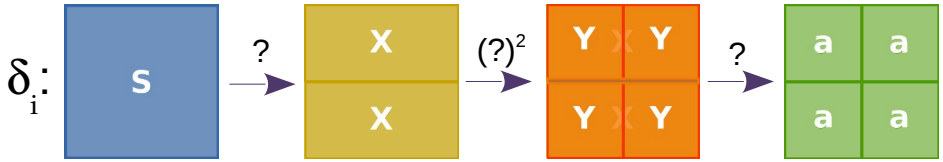

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- **E-step**: starting from an estimate of θ_g, calculate the expected usage counts $\hat{c}(X \to \lambda)$ of each rule
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- **M-step: r**e-estimate the rule probabilities θ_g:

$$\hat{P}(X \to \lambda) = \frac{\hat{c}(X \to \lambda)}{\sum_{\mu} \hat{c}(X \to \mu)}$$

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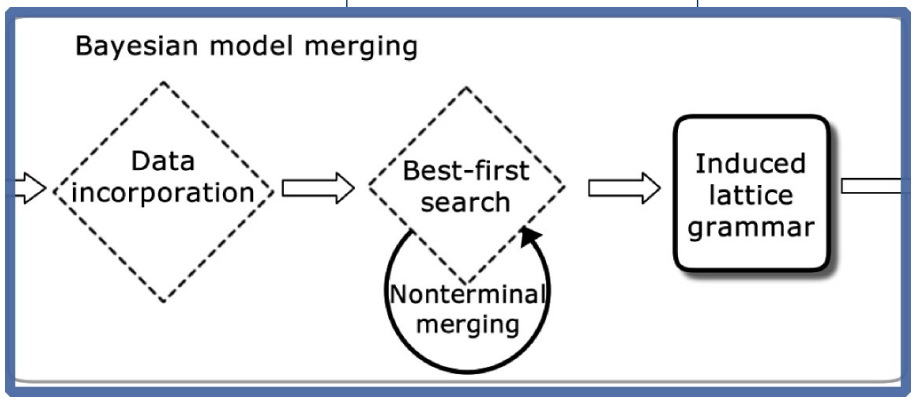
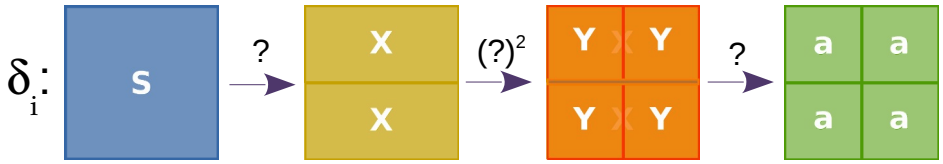


2D Earley parsing



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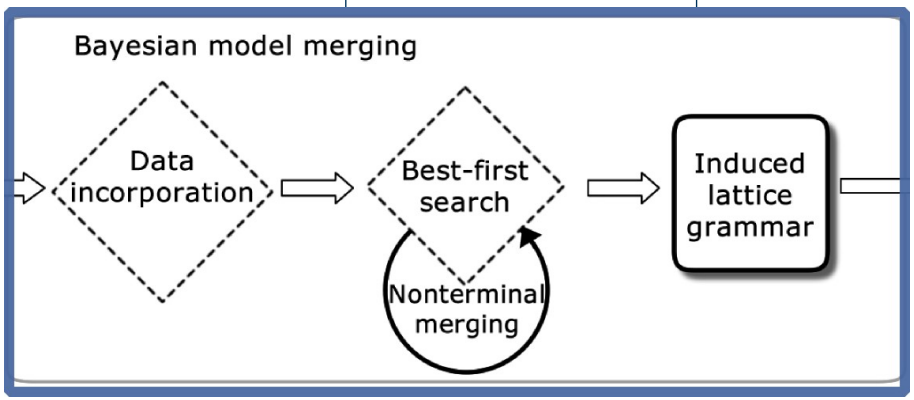

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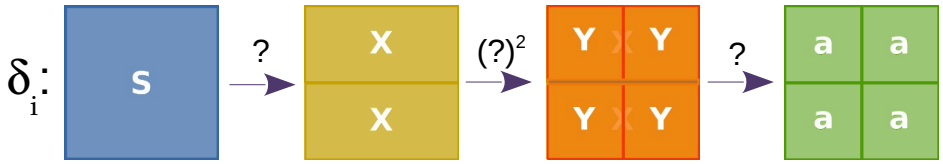

$P(\delta_i)=?$

- How to find the Viterbi derivations in the E-step?
- Generalizing the Earley's string parser (Earley, 1970) to 2D
  - Top-down parsing algorithm
  - Worst-case complexity is $O(n^3)$, but usually performs better
    - e.g. $O(n^2)$ for unambiguous grammars
  - Does not require the grammar to be in CNF
  - Calculation of Viterbi probabilities with the extension of (Stolcke, 1994)

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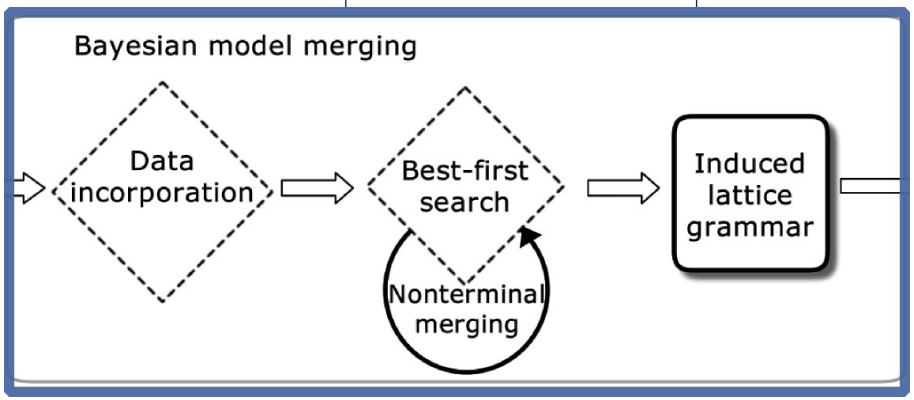

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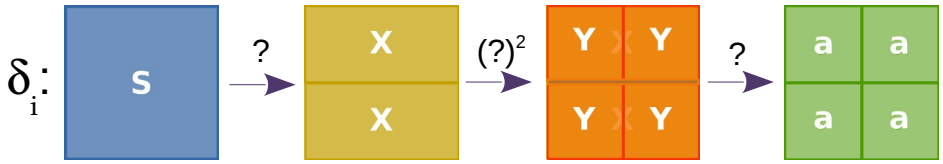

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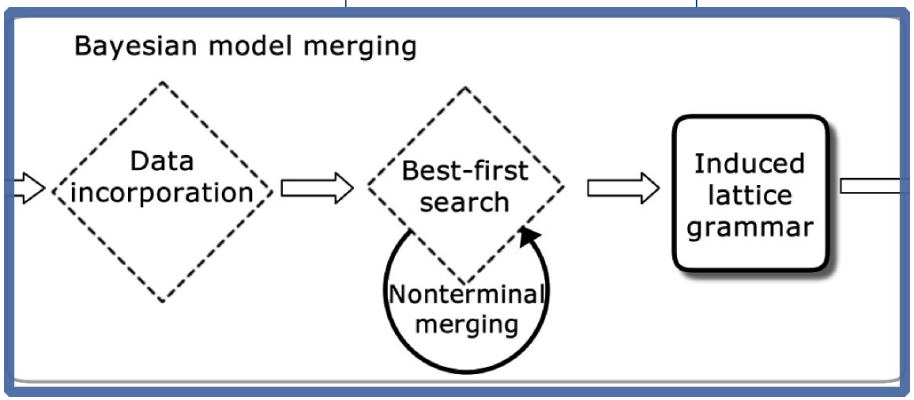
A. Martinović and L. Van Gool. Earley parsing for 2D stochastic context free grammars. Technical Report KUL/ESAT/PSI/1301, KU Leuven, 2013.

Search in model space



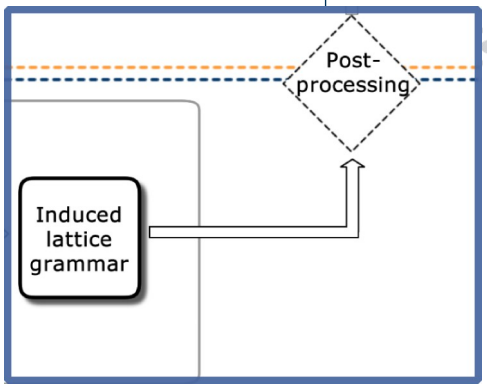
- Posterior calculation is modified using a global prior weight *w*
- Minimizing the energy

$$E(G \mid D) = - w \log P(G) - \log P(D \mid G)$$

  - *w* small: low generalization, search procedure stops earlier
  - *w* large: increasing the tendency to generalize beyond data

- Greedy best-first search
  - In each iteration, every pair of nonterminals is considered for merging
  - All candidate grammars are evaluated
  - The candidate grammar with minimum energy is accepted if this energy is lower than the current grammar's
  - The rule probabilities are learned in each step using the EM procedure

Obtaining the final model



- Casting the induced grammar back to image space
  1. Sequences of the same nonterminal symbol are collapsed, e.g.

$X \rightarrow \lambda YYy \;\; \{\{s_1, y_1, y_2, s_2\}\} \xrightarrow{\text{collapse}} X \rightarrow \lambda Yy \;\; \{\{s_1, y_1 + y_2, s_2\}\}$

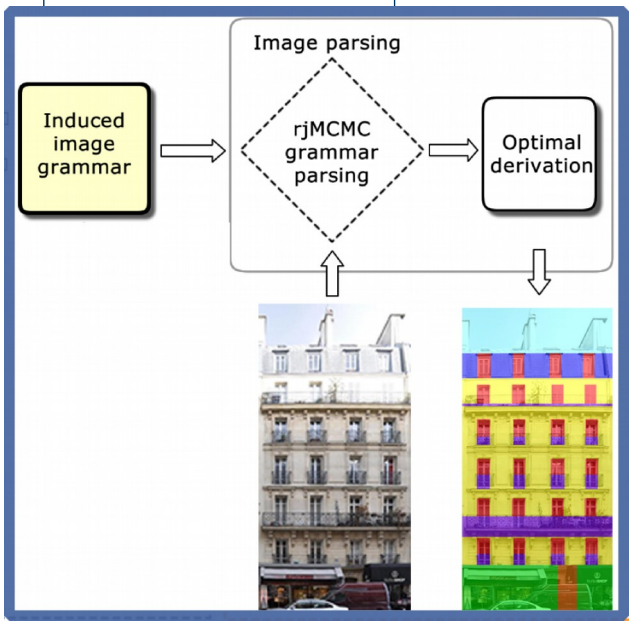
  2. For every rule $p = (X \rightarrow \lambda_1 \ldots \lambda_k)$, we fit a (k-1)-variate Gaussian distribution $\phi(A) = \mathcal{N}(\bar{\mu}, \hat{\Sigma})$ to the set of its attributes $A(p) = \{\alpha_1 \ldots \alpha_n\}$

$$\bar{\mu} = \frac{1}{n} \sum_{j=1}^{n} \alpha_j$$

$$\hat{\Sigma} = \frac{1}{n-1} \sum_{j=1}^{n} (\alpha_j - \bar{\mu})(\alpha_j - \bar{\mu})^T$$

  - This enables us to sample productions with continuous attributes in image space

Parsing in image space



- Find the grammar derivation δ which optimally describes the image
- Optimization is difficult:
  1. Rule attributes can have continuous values
     - Solution: Markov Chain Monte Carlo (MCMC) reduces optimization to sampling
  2. Grammar is stochastic, the number of rules per derivation can change
     - Solution: Reversible jump MCMC (rjMCMC)
- Posterior of a derivation δ given an image I:

$$P(\delta|I) \propto \underbrace{P(I|\delta)}_{\text{Likelihood}} \underbrace{\prod_{s\in\delta} P(r_s) \prod_{s\in\delta} \phi(A(r_s))}_{P(\delta)}$$

Rule term — Attribute term — Prior

Parsing in image space

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Rule term

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Likelihood

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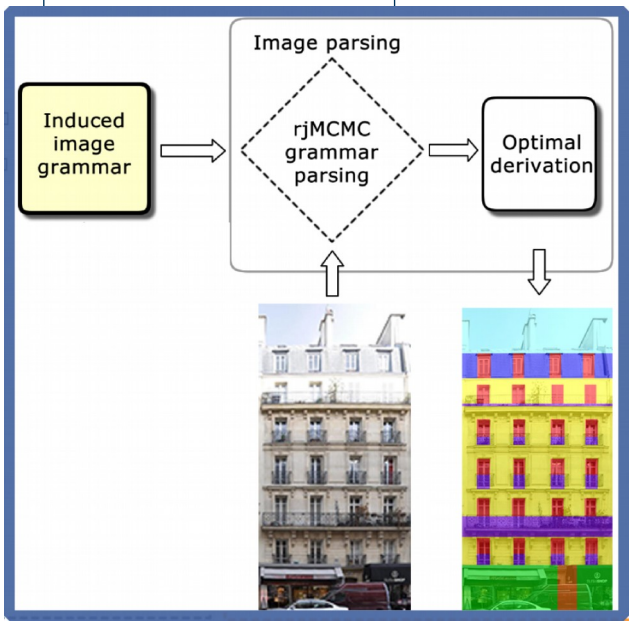

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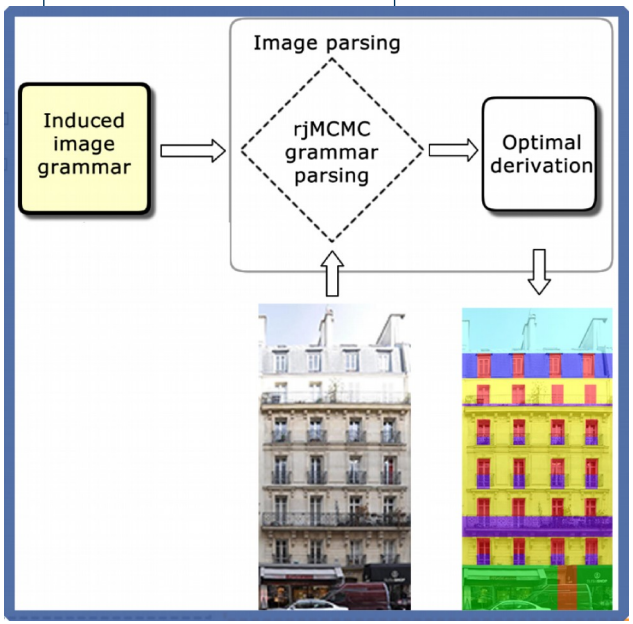

- Boltzmann's transformation:

- Rule term: sum of negative log probabilities of all rules in derivation δ
- Attribute term: discrepancy between proposed and expected attributes
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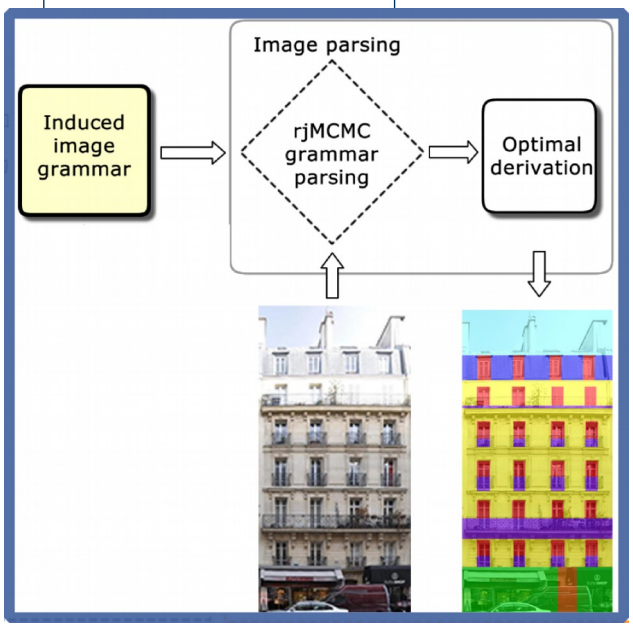
Parsing in image space



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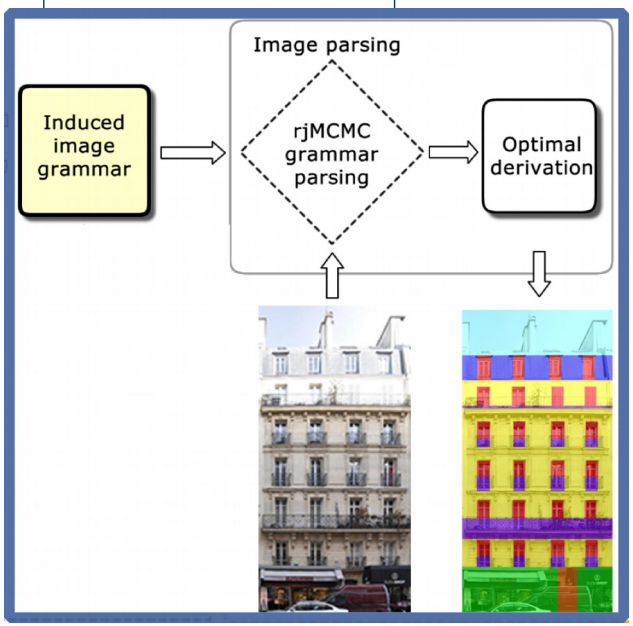

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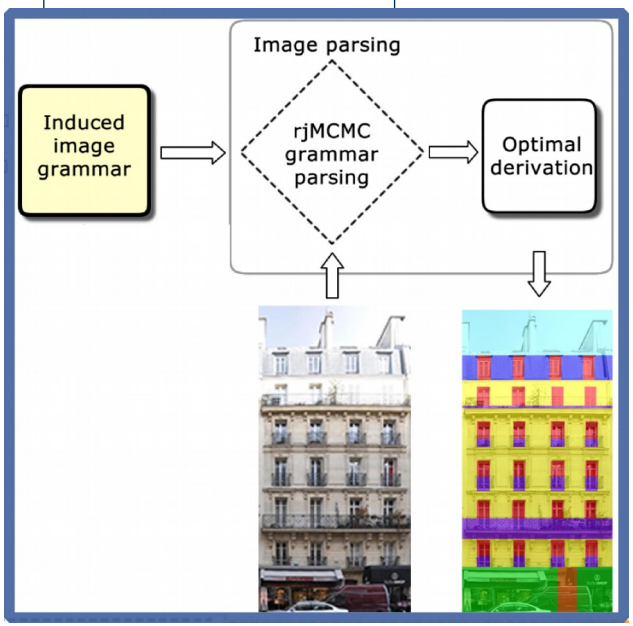

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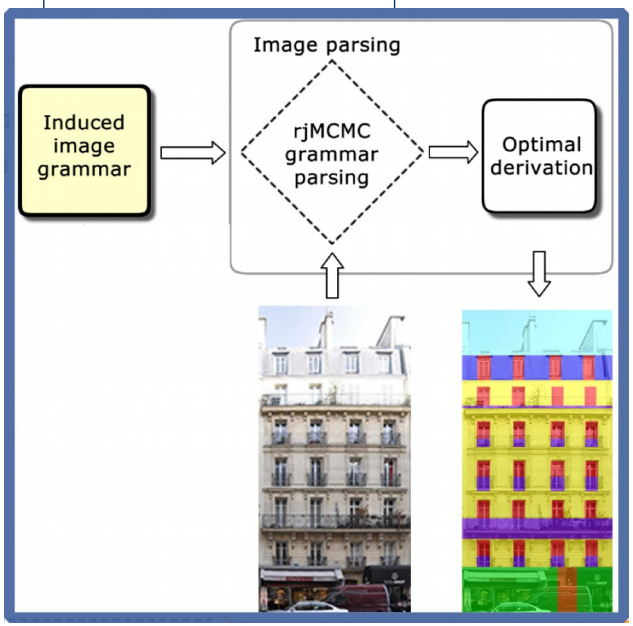

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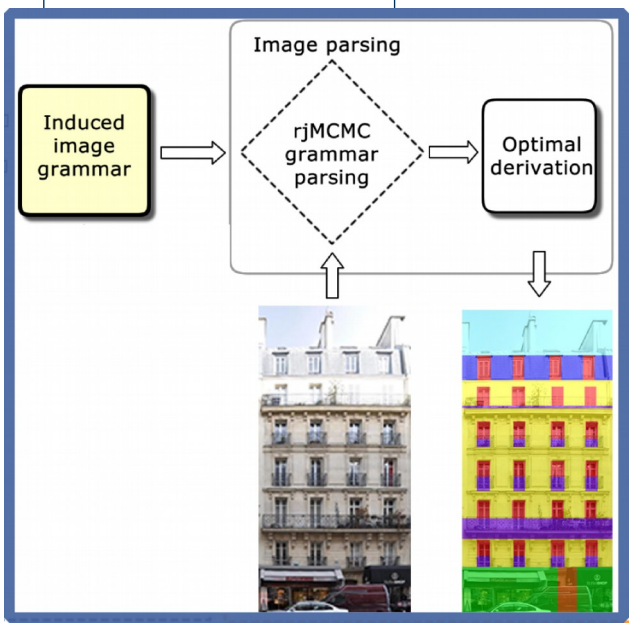

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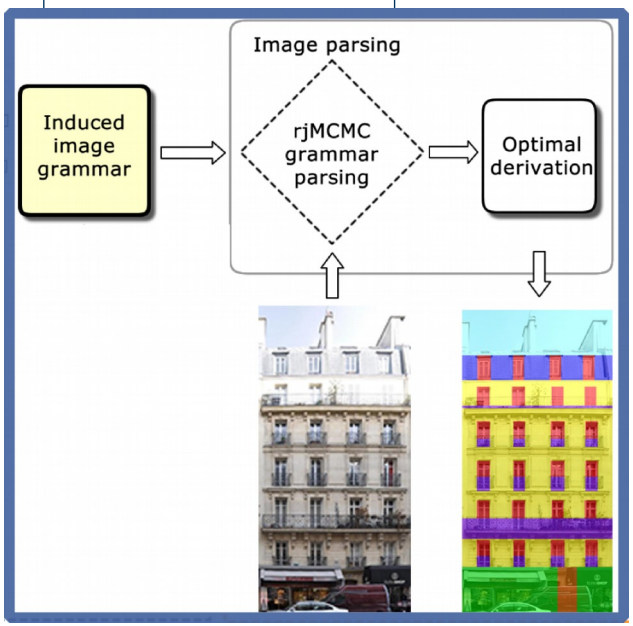

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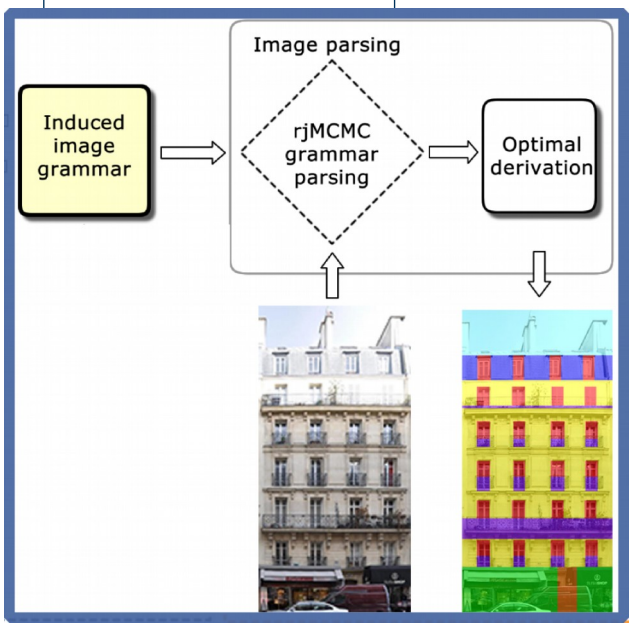

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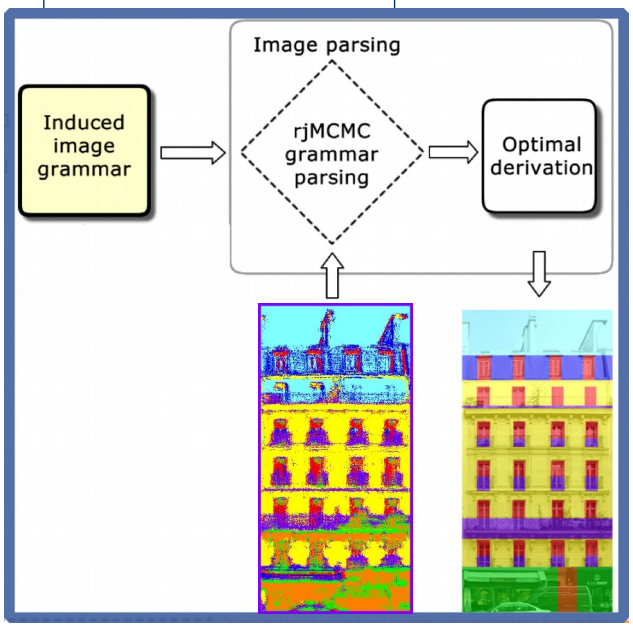

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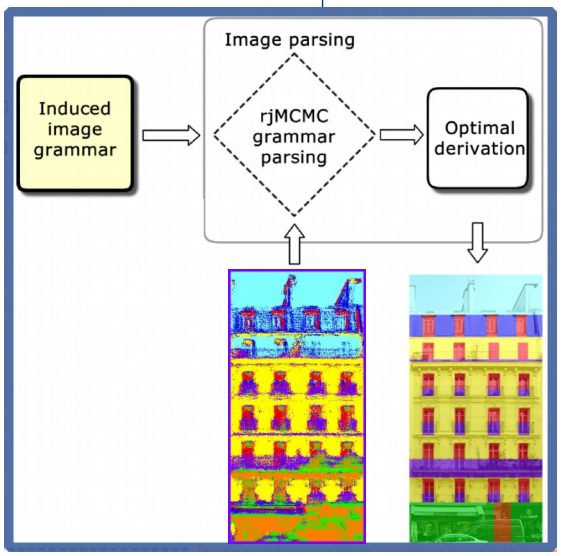
Parsing in image space - rjMCMC



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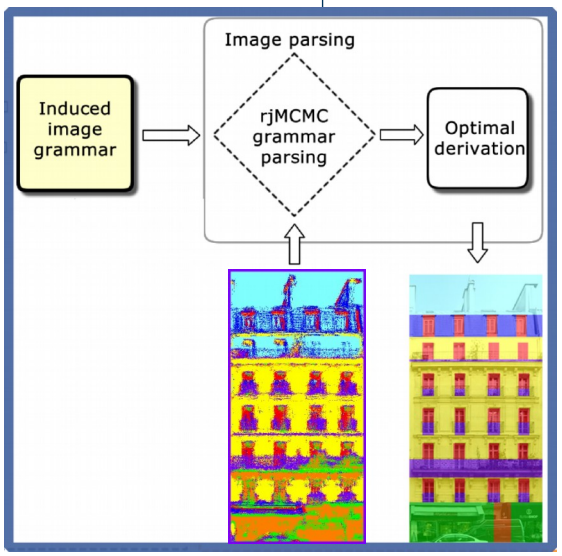

- rjMCMC with Metropolis-Hastings update
- Markov chain is initialized with a random derivation

- Two possible moves in every iteration:
  - **Diffusion** move – parse tree doesn't change, dimensionality of α is preserved
  - **Jump** move – a rule in the tree is resampled, dimensionality of α changes
- Improvements:
  - **Parallel tempering** – 8 chains are run in parallel on different cooling schedules
  - **Delayed rejection –** a jump move is always followed by a diffusion move, and the moves are accepted or rejected in unison

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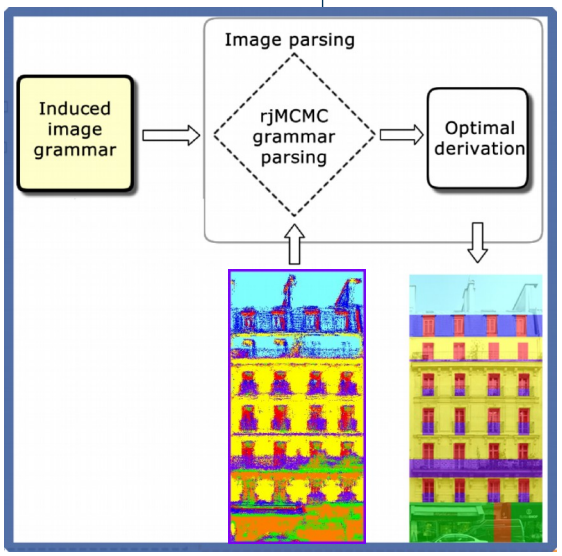

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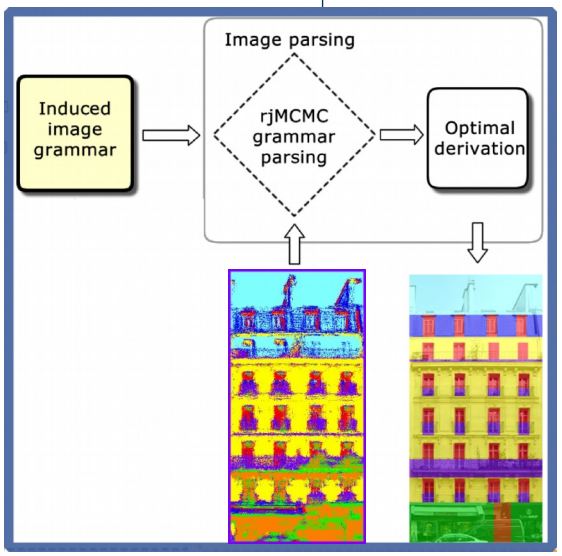

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$$\delta = (\tau, \alpha)$$

Parse tree

"Parameter vector"
Concatenated attributes
in a pre-order traversal of τ

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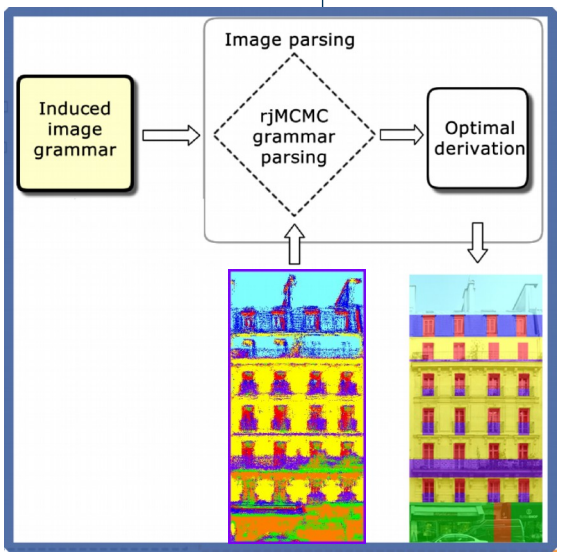

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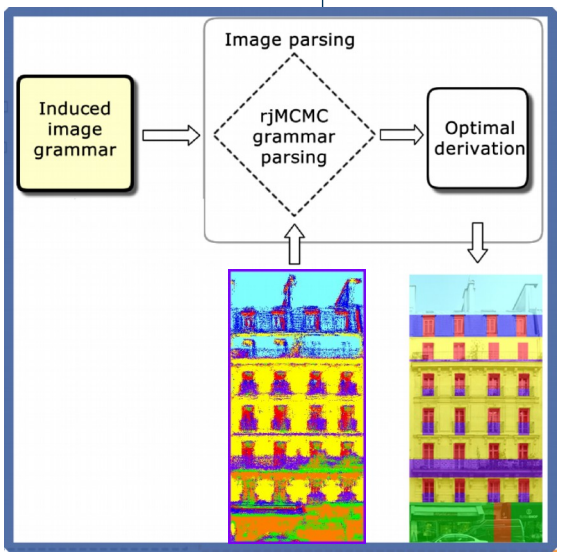

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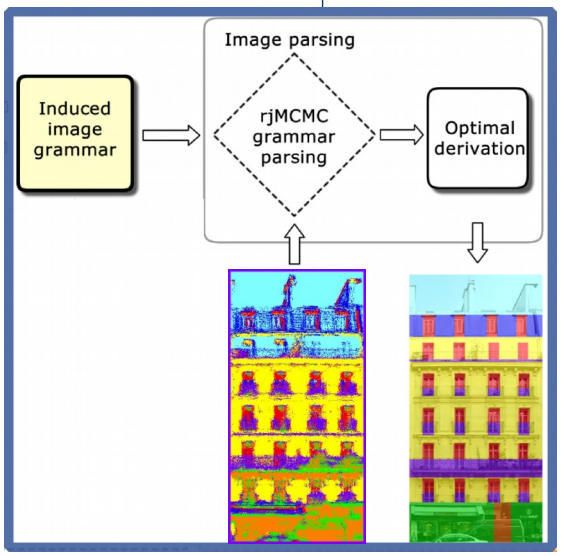
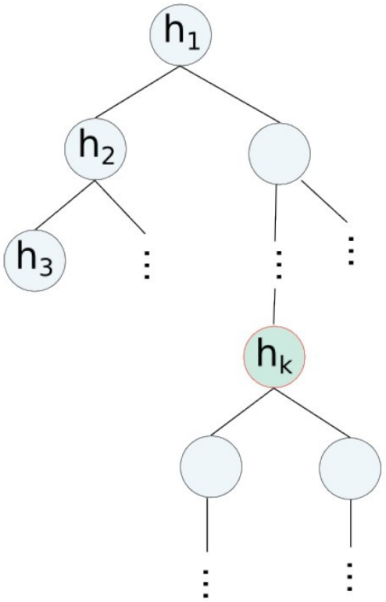
rjMCMC diffusion move

- Select a random node h_k in the derivation tree
- Sample from a Gaussian proposal distribution centered on the current parameters



$\delta=(\tau,\alpha)$

τ:



Starting α:

$[\underbrace{\alpha_1\alpha_2\ldots\alpha_{n_1}}_{h_1}\ \underbrace{\alpha_{n_1+1}\ldots\alpha_{n_2}}_{h_2}\ \ldots\ \underbrace{\alpha_{n_{k-1}}\ldots\alpha_{n_k}}_{h_k}\ \ldots]$

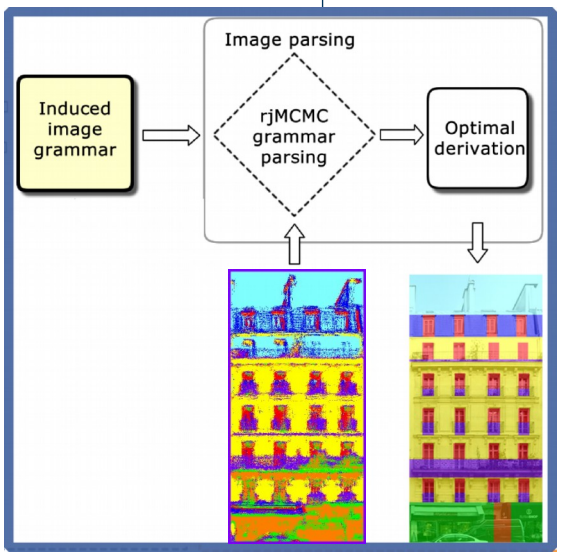
Diffusion move to α':

$[\underbrace{\alpha_1\alpha_2\ldots\alpha_{n_1}}_{h_1}\ \underbrace{\alpha_{n_1+1}\ldots\alpha_{n_2}}_{h_2}\ \ldots\ \underbrace{\alpha'_{n_{k-1}}\ldots\alpha'_{n_k}}_{h_k}\ \ldots]$

Acceptance probability of the move

$$\rho_{\delta\to\delta'} = min\{1, \frac{p(\delta'|I)}{p(\delta|I)}\} = min\{1, e^{-(E_{\delta'}-E_\delta)}\}$$

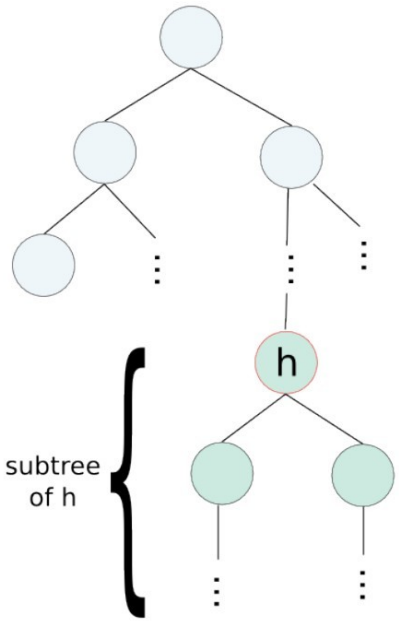
rjMCMC jump move



- A random node h is selected in the derivation tree
- A new rule is sampled from all rules applicable to selected LHS
- If RHS has different length, the whole subtree rooted on h is re-derived
  - Topology of τ changes
  - Dimensionality of α changes

$\delta=(\tau,\alpha)$

τ:



Starting α:

$[\alpha_1\alpha_2...\alpha_l \underbrace{\alpha_{l+1}...\alpha_{l+d_1}}_{\text{in subtree of h}} \alpha_{l+d_1+1}...\alpha_n]$

Jump move to α':

$u = [u_1..u_{d_2}]$

$\alpha' = [\alpha'_1\alpha'_2...\alpha'_l \alpha'_{l+1}...\alpha'_{l+d_2} \alpha'_{l+d_2+1}...\alpha'_m]$

$= [\alpha_1\alpha_2...\alpha_l \quad u_1..u_{d_2} \quad \alpha_{l+d_1+1}...\alpha_n]$

$u' = [\alpha'_{l+1}...\alpha'_{l+d_2}]$

Acceptance probability of the move

$$\rho_{\delta\to\delta'} = min\{1, \frac{q_{\tau'}(h)}{q_\tau(h)} e^{-[(E^{img}_{\delta'}+E^{attr}_{\delta'})-(E^{img}_{\delta}+E^{attr}_{\delta})]}\}$$

Probability of choosing a nonterminal h in tree τ

Image and attribute terms

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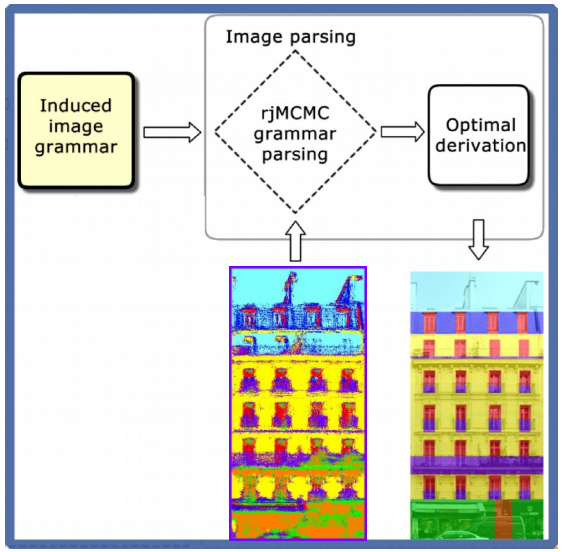
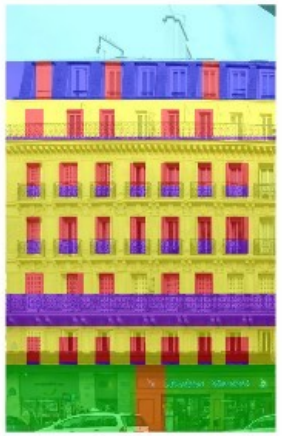
Parsing results

- ECP dataset
- Example: fold 1

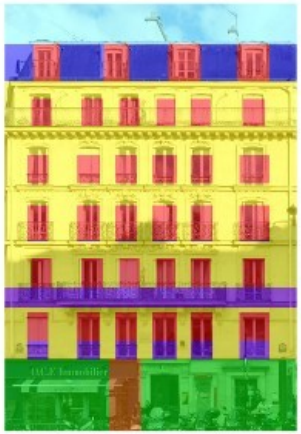



monge_1


monge_3


monge_6

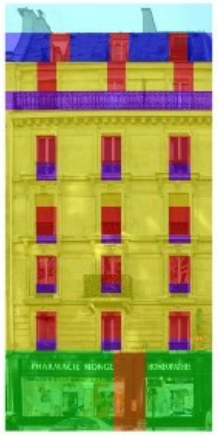

monge_9


monge_29bis


monge_61

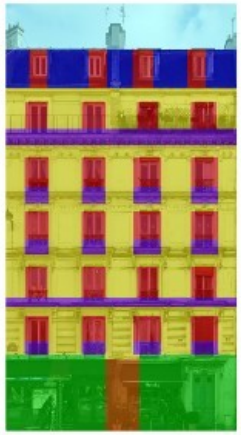

monge_65


monge_71

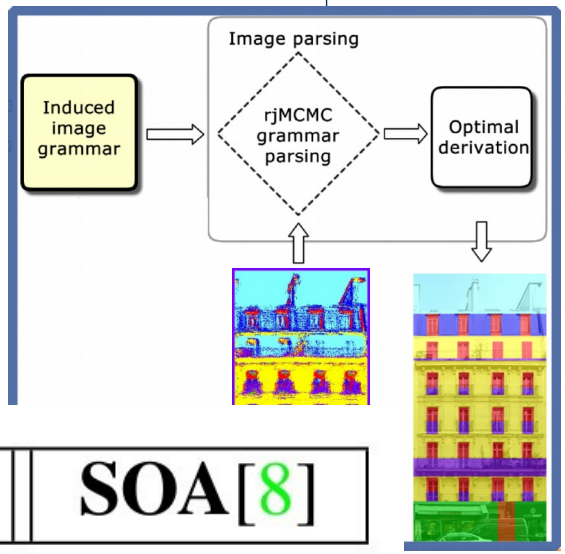

monge_74


monge_79bis


monge_86


monge_101

Parsing results



- Quantitative analysis

Class	RF[22]	RL[21]	Ours	SOA[8]
Window	29	62	66	75
Wall	58	82	80	88
Balcony	35	58	49	70
Door	79	47	50	67
Roof	51	66	71	74
Sky	73	95	91	97
Shop	20	88	81	93
Overall	48.55	74.71	74.82	84.17

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VISICS

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Generating novel designs

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Generating novel designs

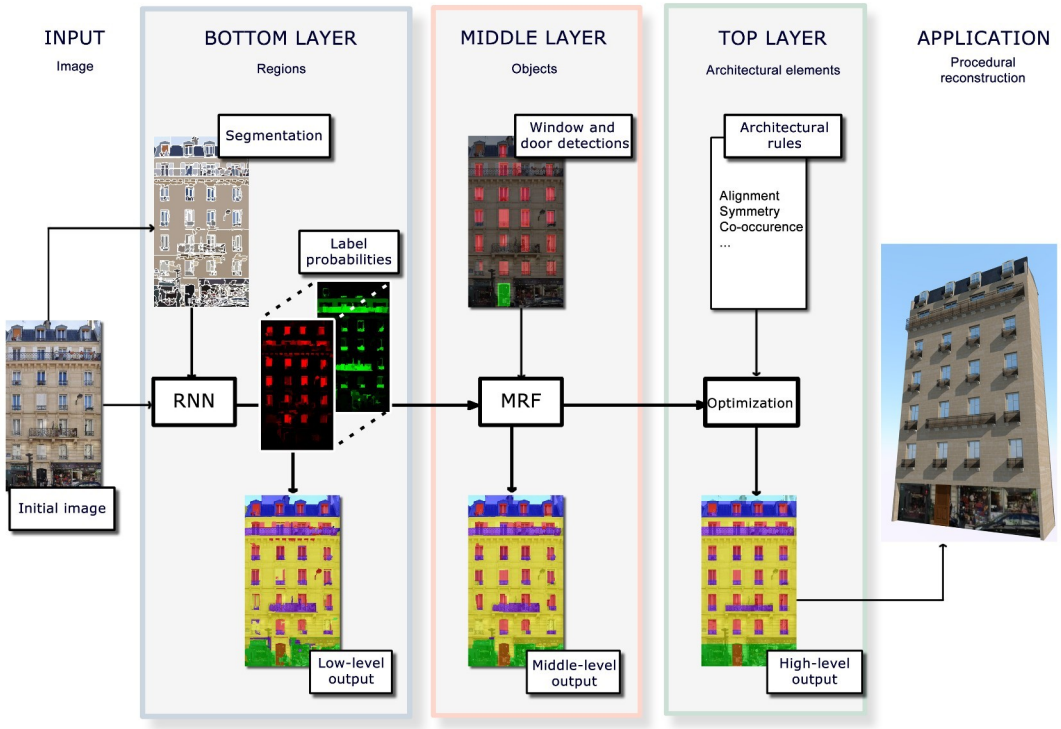
- The effect of prior weight *w* on grammar generalization

w=1.0

w=0.3

Future work

- State of the art in facade parsing
  - Images → Labelings
- This paper
  - Labelings → Grammar
- Combine the two approaches
  - “Facade bootstrapping”



A. Martinović, M. Mathias, J. Weissenberg, and L. Van Gool. A three-layered approach to facade parsing. In ECCV, 2012

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Thank you