GeoX Young Academy: Machine Learning in Remote Sensing Best practice and recent developments - Part 3: ML and Images

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Overview

1. Random Forests
   - Fusion
   - Node Tests
   - Interpretation
   - Application Tips
2. Graphical Models
   - Motivation
   - MRF
   - Application
   - Example
3. ConvNets
   - MLP to ConvNet
   - Convolution
   - Architectures
   - Auto Encoder
   - Frameworks

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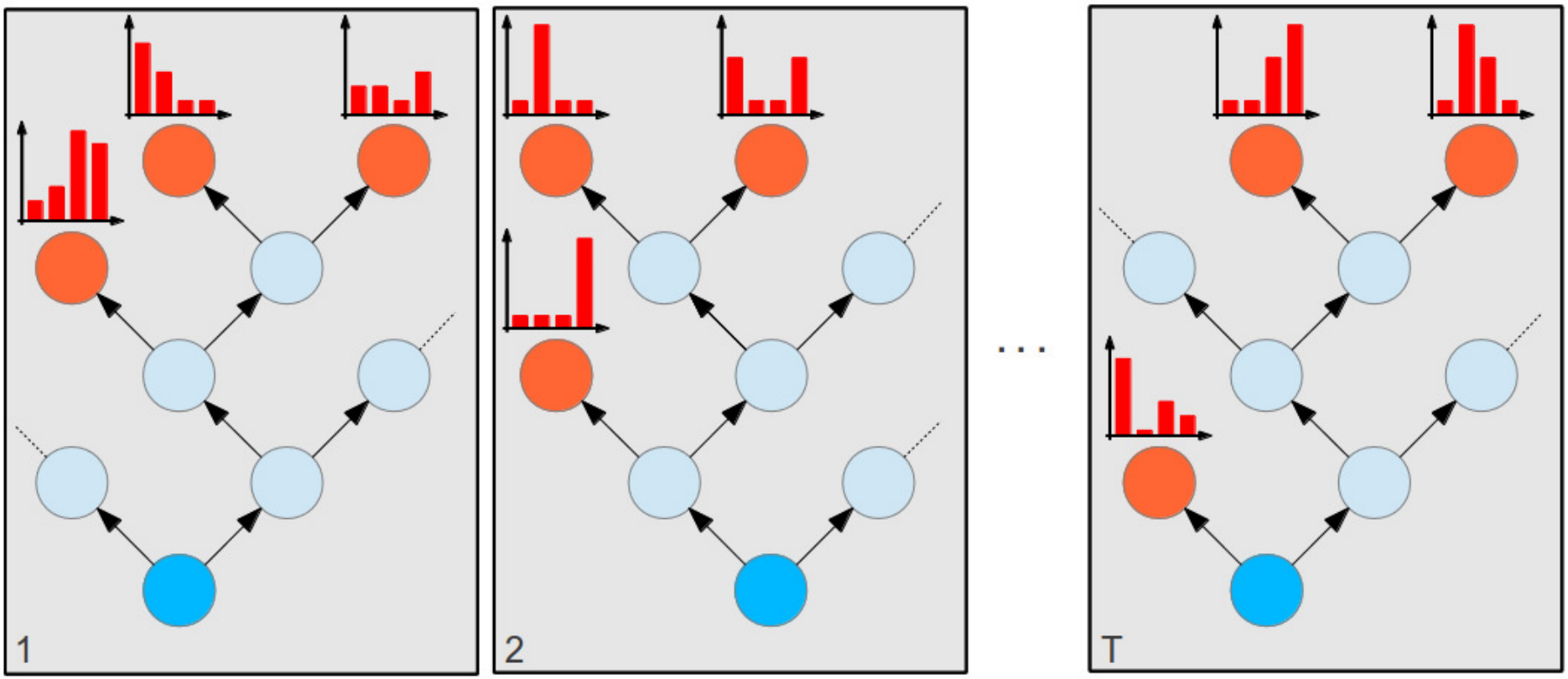
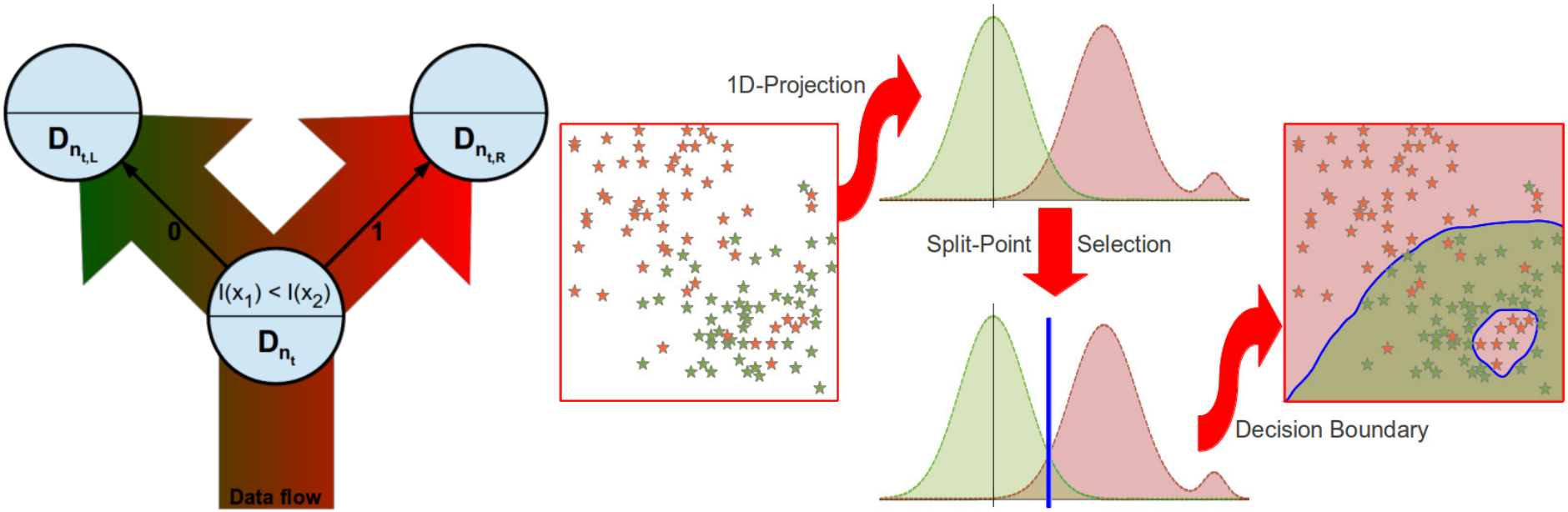
Recap



Set of decision trees

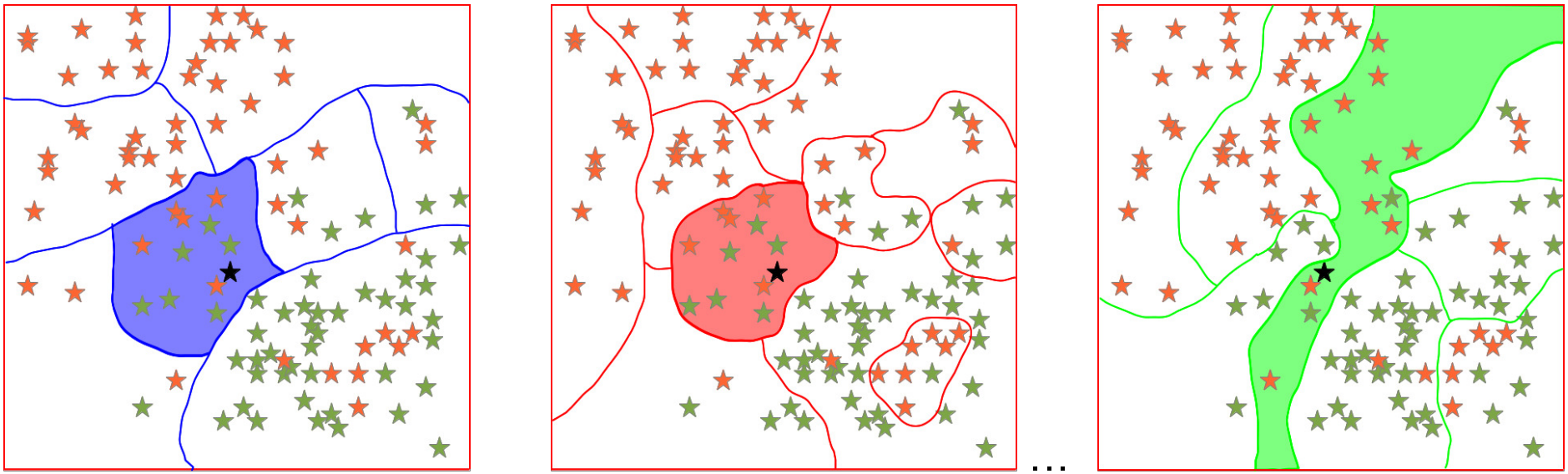
- Each tree t generated from training data $\mathrm{D}_t \subseteq \mathrm{D} \subset \mathbb{D}$
- Creation of one tree independent of all other trees
- Based on random processes to produce diverse set of trees

Data Propagation



- Data enters each tree in root node
- Each non-terminal / internal node performs a (simple) binary test
- Data propagation is based on test outcomes

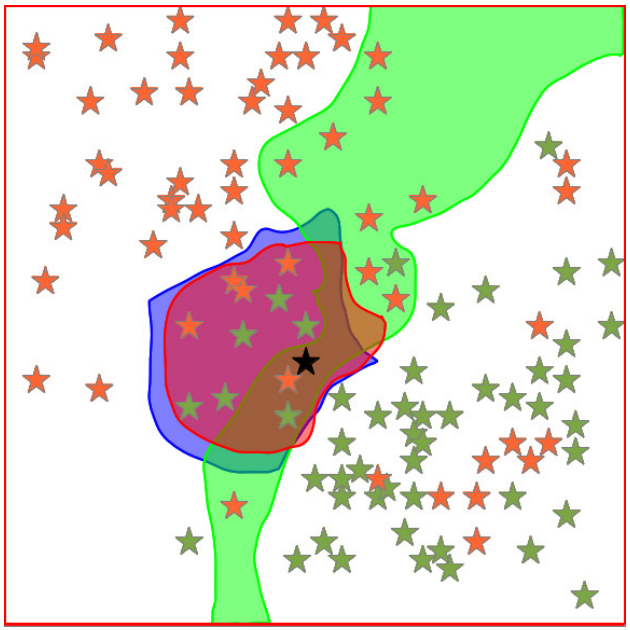
Tree Fusion



$t = 1$ $t = 2$ ... $t = T$

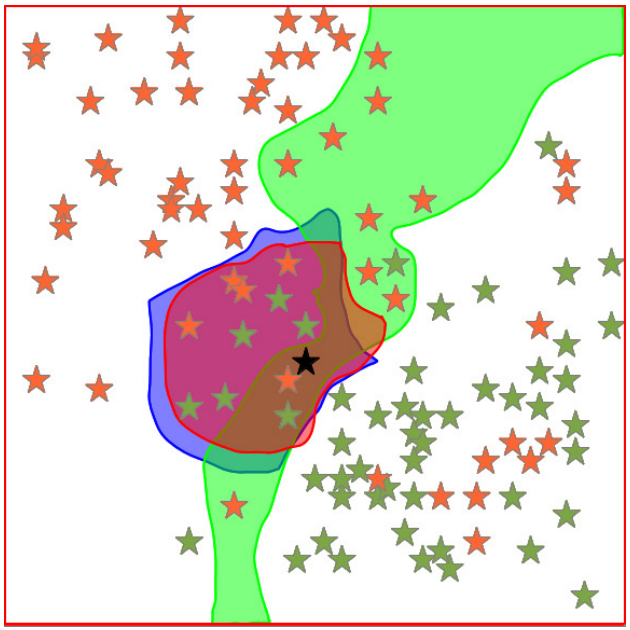
- Query sample is propagated through all trees
- Reaches exactly one leaf in each tree
- Information about target variable assigned to these leafs need to be combined

Tree Fusion



How to combine information assigned to individual leafs?

Tree Fusion

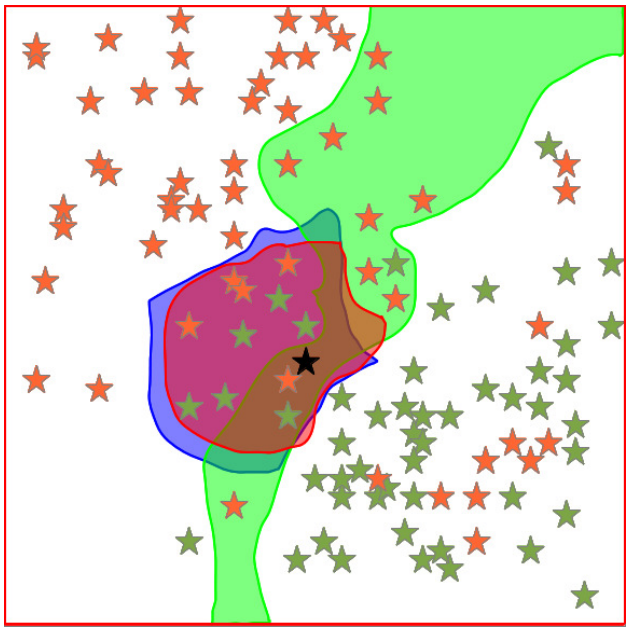


Random Forests

$$P(c|x) = \frac{1}{T} \sum_{t=1}^{T} \delta(M(n_t), c)$$

$M(n)$ is dominant class
of samples in leaf node n

Tree Fusion

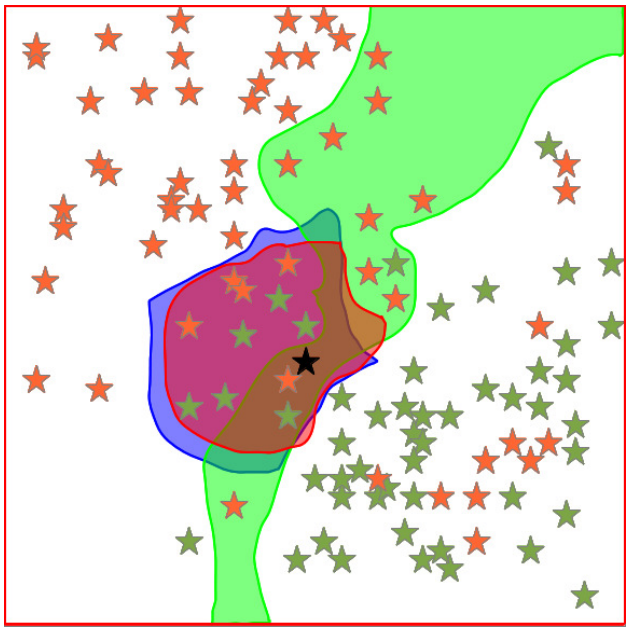


Randomized Trees

$$P(c|x) = \frac{1}{T}\sum_{t=1}^{T} P_t(c|x)$$

$P_t(c|x)$ is class posterior in leaf node n_t

Tree Fusion



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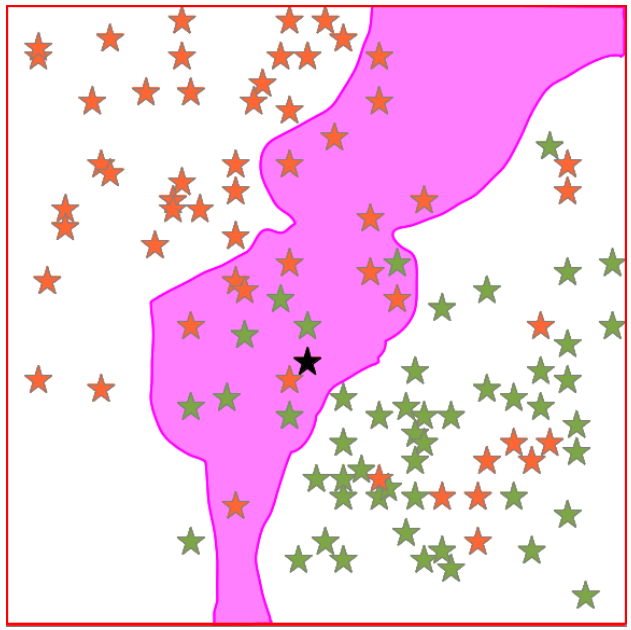
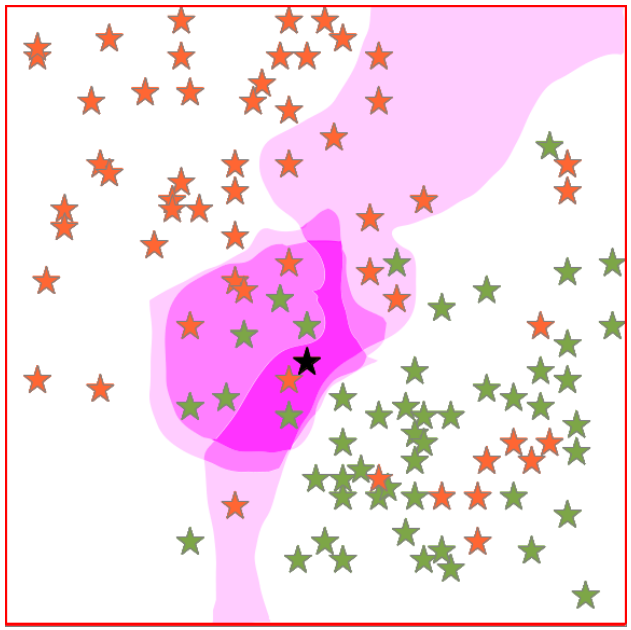


Fuse before estimation:

$$D_{L_x} = \bigcup_{t=1}^{T} D_{n_t}$$

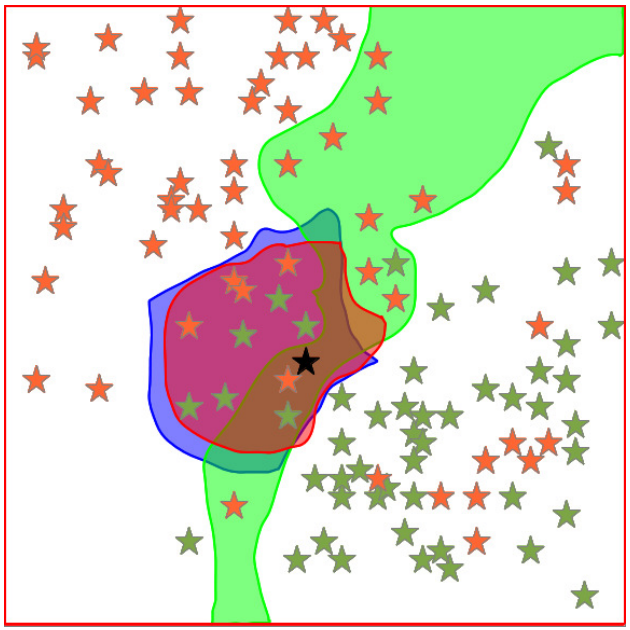
(Multi-set)



$$P(c|x) = \frac{P(L_x|c)P(c)}{P(L_x)}$$

(Details in [Hänsch, 2014])

Tree Fusion



Randomized Trees

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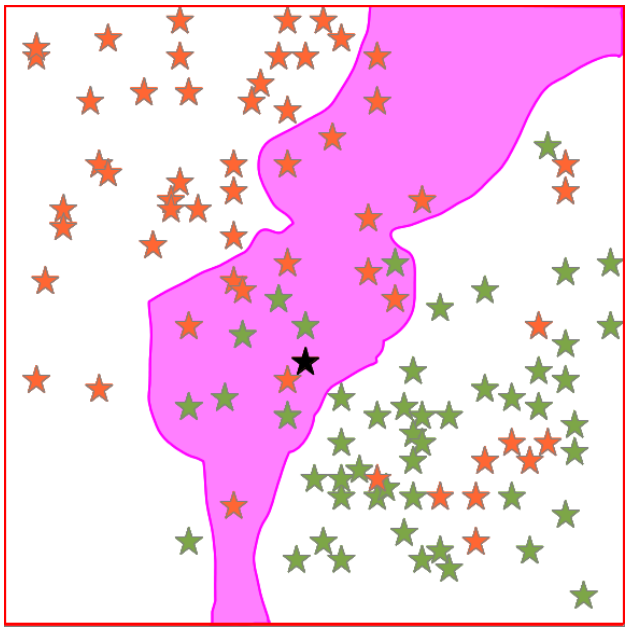

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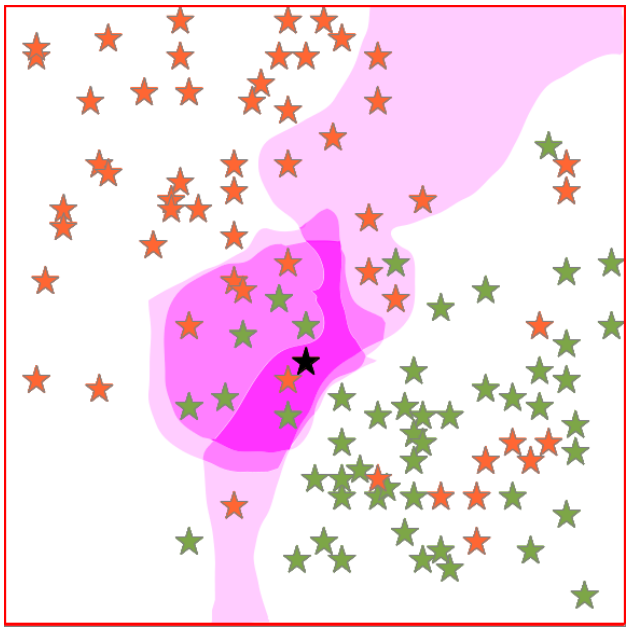


Weighted fusion.

$$P(c|x) = \sum_{t=1}^{T} w_t P_t(c|x)$$

(Details in [Hänsch, 2014])

Node tests

Concatenation of several functions with different tasks

$t_\tau : \mathbb{D} \rightarrow \{0, 1\}$ $\quad \tau \in \mathrm{T} \equiv$ Parameter set

$t_\tau = \xi \circ \psi \circ \phi$

$\phi : \mathbb{D} \rightarrow \mathbb{R}^n \equiv$ Implicit feature extraction

e.g. $x \in \mathbb{R}^n : \ \phi : \mathbb{R}^n \rightarrow \mathbb{R}^2, x \mapsto (x_i, x_j)^T$

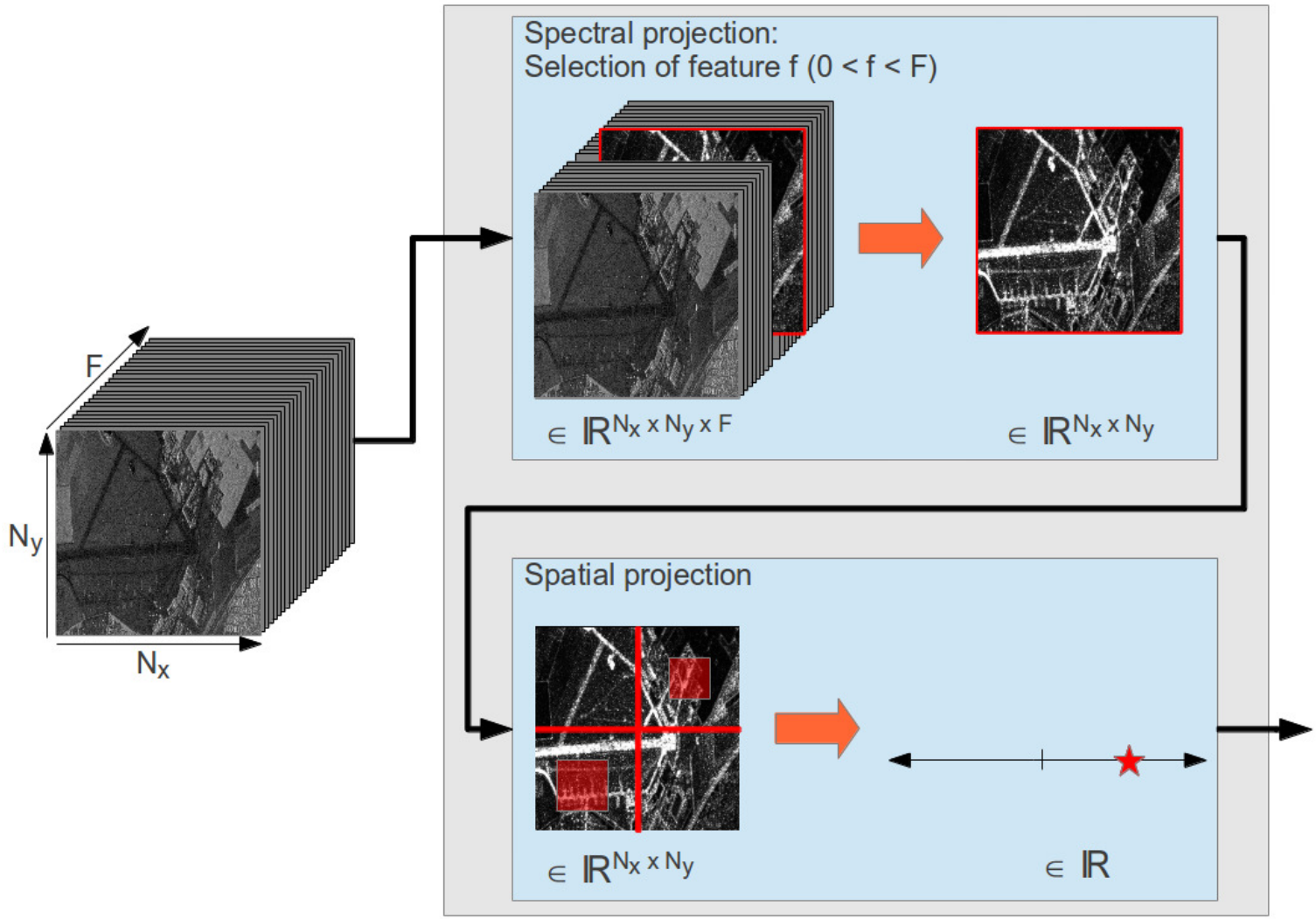
$\psi : \mathbb{R}^n \rightarrow \mathbb{R} \equiv$ Feature fusion

e.g. $\phi(x) \in \mathbb{R}^2 : \ \psi : \mathbb{R}^2 \rightarrow \mathbb{R}, \phi(x) \mapsto [\psi_i, \psi_j] \cdot \phi(x)$

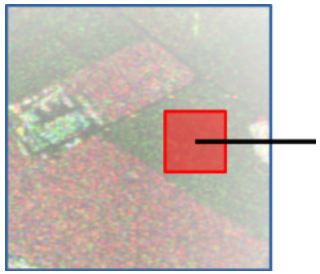
$\xi : \mathbb{R} \rightarrow \{0, 1\} \equiv$ Child node assignment

e.g. thresholding

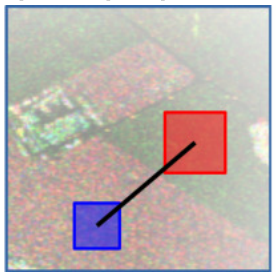
Implicit Feature Extraction



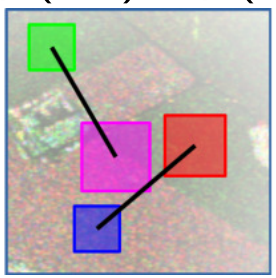
Implicit Feature Extraction



$d(op(R), ref)$



$d(op(R_1), op(R_2))$

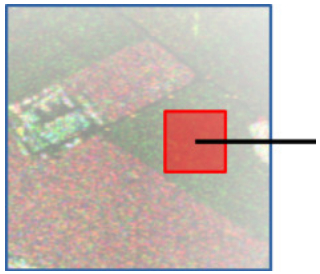


$d(op(R_1), op(R_2)) - d(op(R_3), op(R_4))$

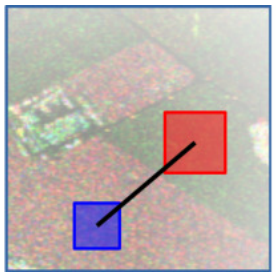
$$t_\tau(\mathbf{x}) = \xi(\psi(\phi(\mathbf{x})))$$

- $\phi : \mathbb{D} \rightarrow \mathbb{R}^n$ can be adopted for different data types
- Region position and size are randomly sampled.
- Different operators *op* (e.g. min, max, selection, averaging, ...)
- Different distance measures *d* (e.g. Euclidean, Frobenius, Bartlet, Wishart, ...)
- Allows RF to work directly on any data type.
- Increases number of possible node tests and thus decreases tree correlation.

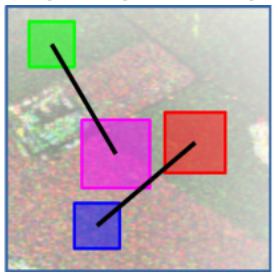
Implicit Feature Extraction



$d(op(R), ref)$



$d(op(R_1), op(R_2))$



$d(op(R_1), op(R_2)) - d(op(R_3), op(R_4))$

$$t_\tau(\mathbf{x}) = \xi(\psi(\phi(\mathbf{x})))$$

Example: Polarimetric SAR data

$\rightarrow$ Patches containing Hermitian matrices

$\rightarrow \mathbf{x} \in \mathbb{C}^{n \times n \times 3 \times 3}$

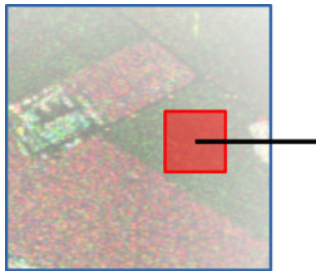
Possible operators

- Select matrix at the center of $\mathbf{x}$
- Average over whole patch
- Select matrix with minimal/maximal span
- ...

Possible distance measures

- Frobenius norm
- Wishart
- Bartlet
- ...

Implicit Feature Extraction



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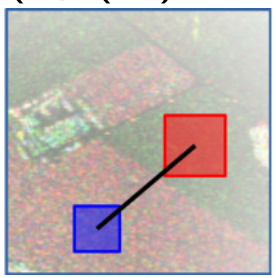
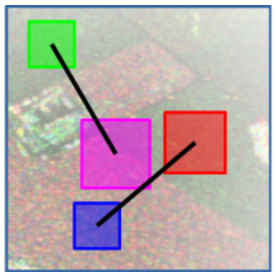
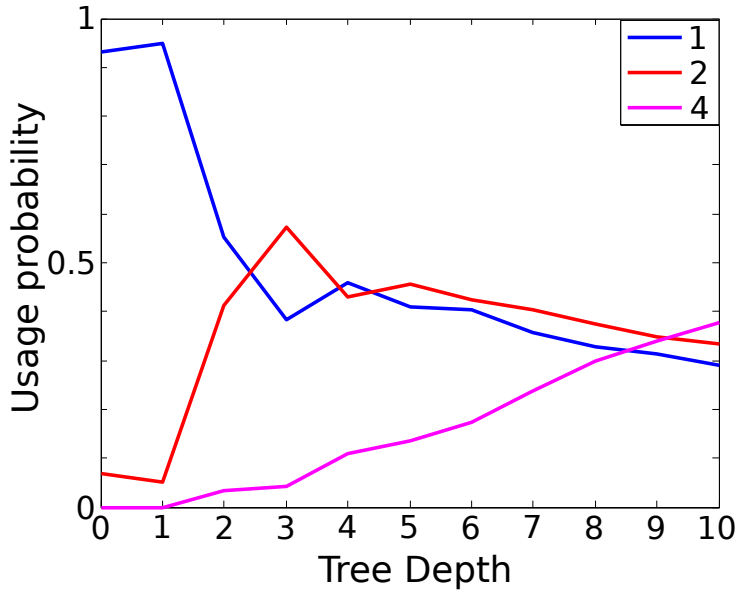


$d(op(R_1), op(R_2))$

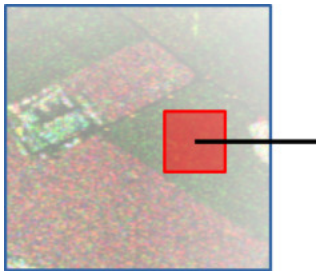


$d(op(R_1), op(R_2)) - d(op(R_3), op(R_4))$



- Works directly on PolSAR data, i.e. no explicit feature extraction
- Automatically selects scale, operators, distance measures, ...
- Reaches competitive results compared to methods based on sophisticated feature extraction

Implicit Feature Extraction



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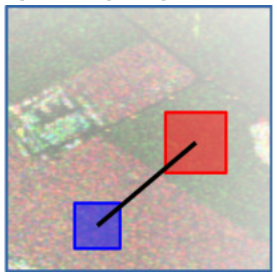
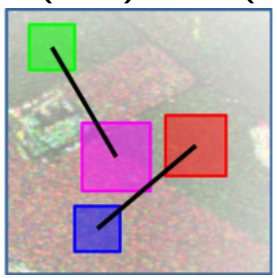
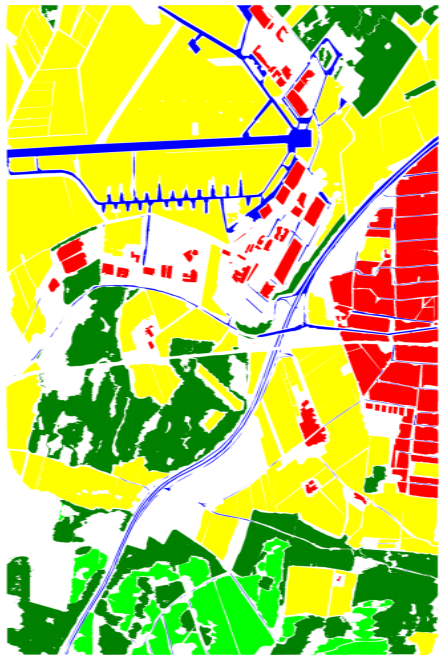


$d(op(R_1), op(R_2))$

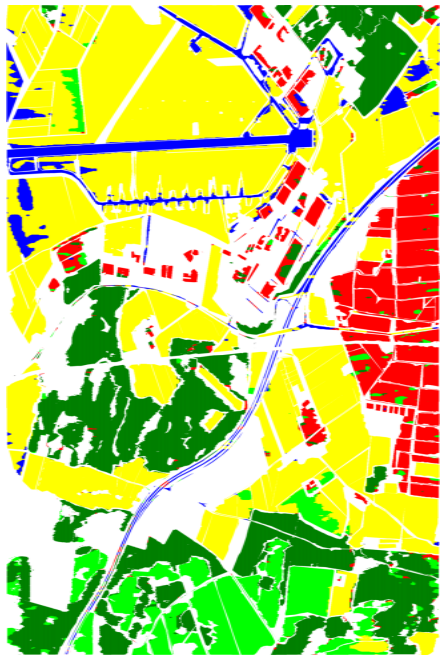


$d(op(R_1), op(R_2)) - d(op(R_3), op(R_4))$

E-SAR, Oberpfaffenhofen



Reference Data
Five classes

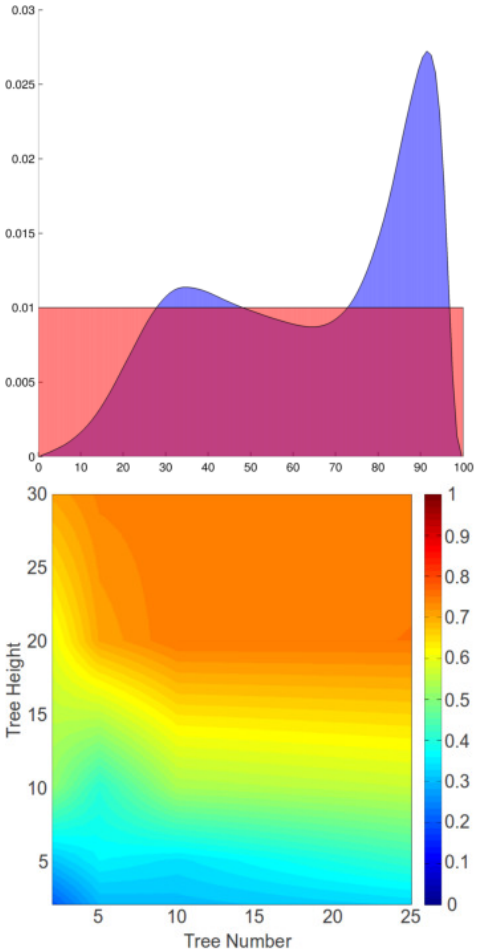


Result
$\sim$ 87% acc.

Random Forests - Split point selection

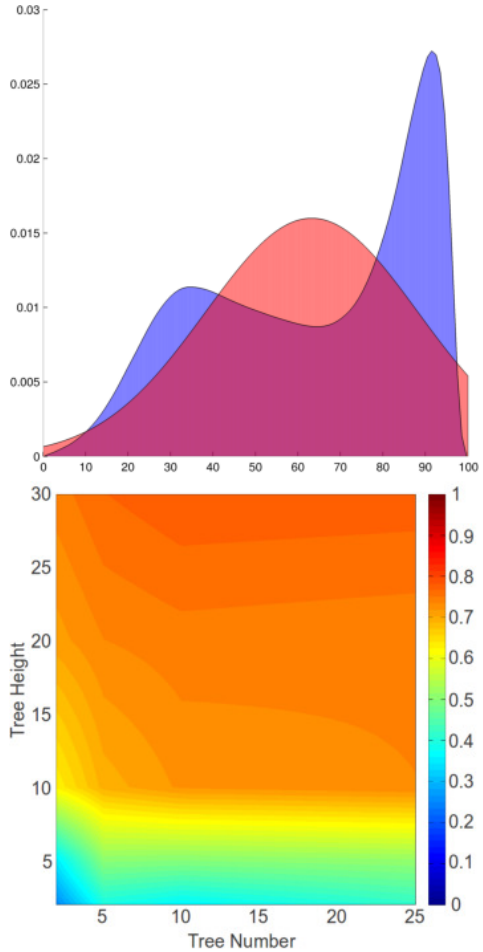
Uniform sampled

$\theta \sim U(\min(\hat{D}), \max(\hat{D}))$



Gaussian sampled

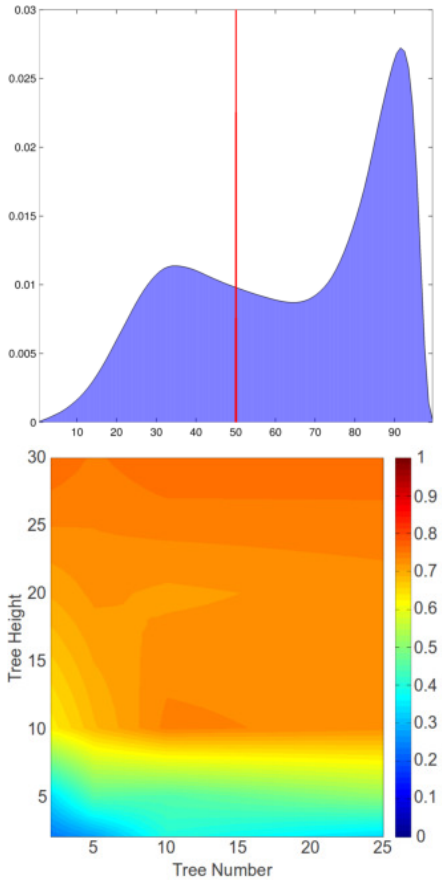
$\theta \sim N(\mu(\hat{D}), \sigma(\hat{D}))$



Random Forests - Split point selection

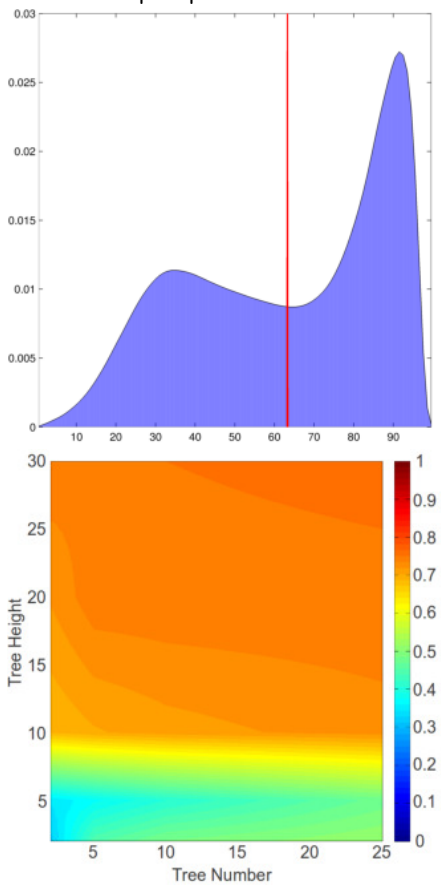
Interval center

$$\theta = \frac{min(\hat{D}) + max(\hat{D})}{2}$$



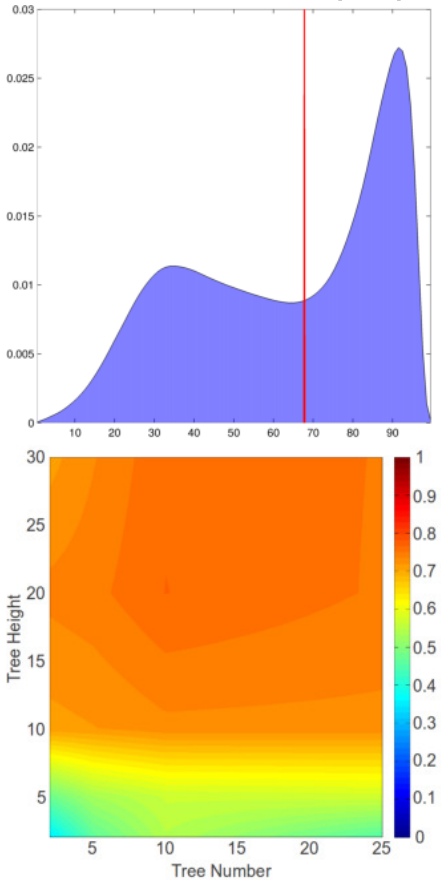
Mean value

$$\theta = \frac{1}{|\hat{D}|} \sum_{x \in \hat{D}} \hat{x}_i$$



Median value

$$\theta = median(\hat{D})$$

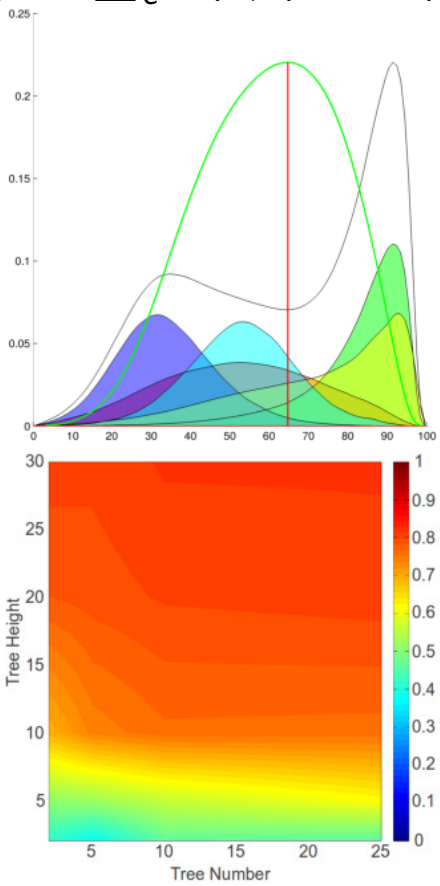


Random Forests - Split point selection

Max. drop of impurity $\theta = \arg\min_{\hat{\theta}} [I(n) - P_L I(n_L) - P_R I(n_R)]$

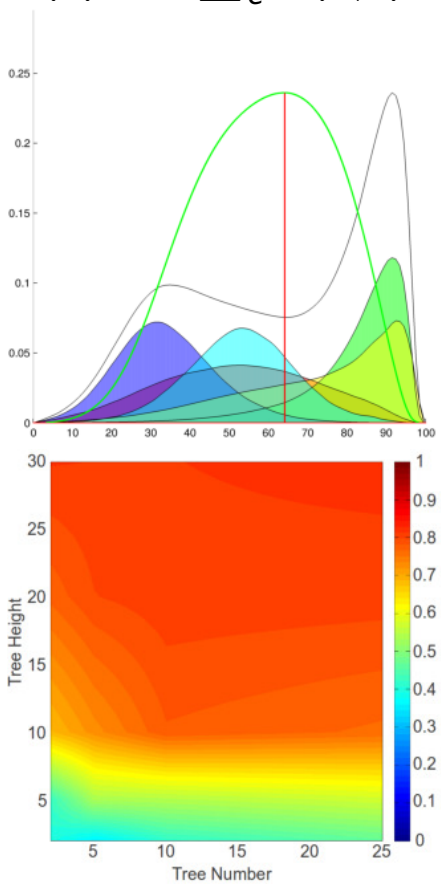
Entropy

$I(n) = -\sum_c P(c|n) \cdot \log P(c|n)$



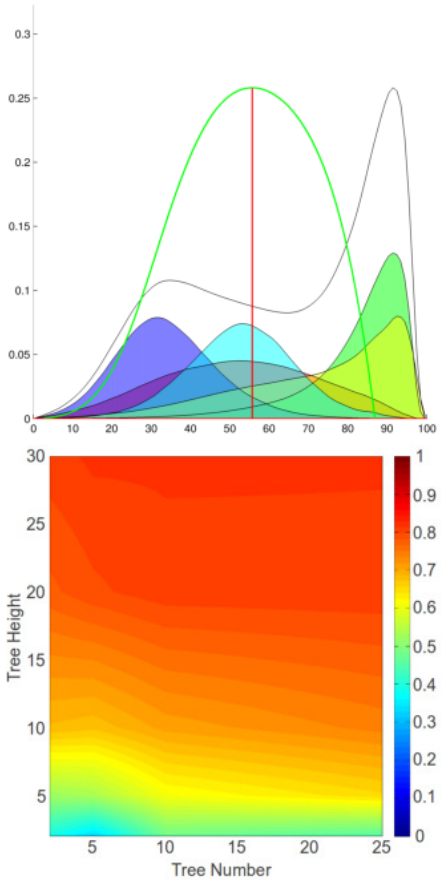
Gini

$I(n) = 1 - \sum_c P(c|n)^2$

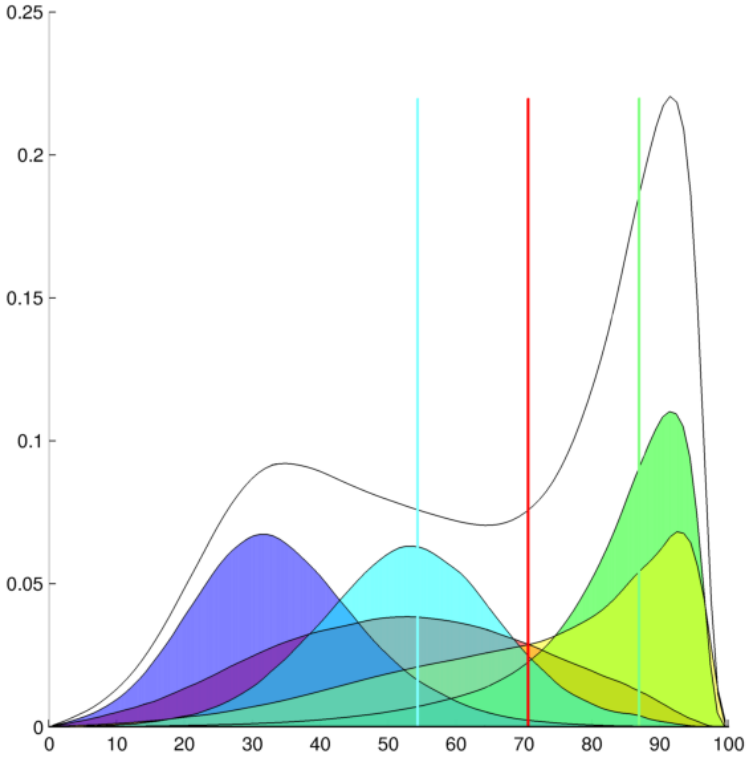


Misclassification

$I(n) = 1 - \max_c P(c|n)$



Random Forests - Split point selection

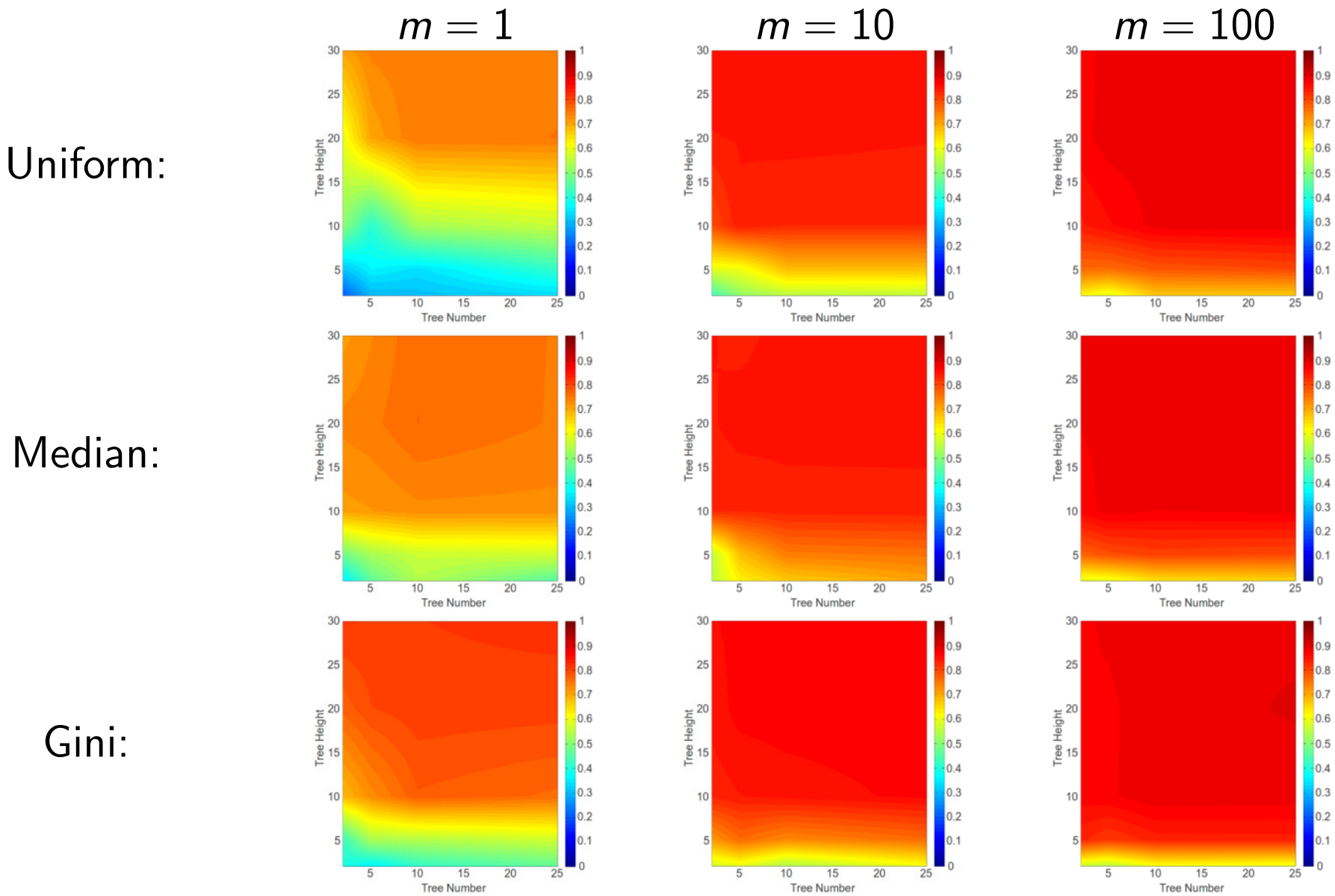


- Other possibilities available
  $\rightarrow$ Intervals, structured label spaces, **inter-class split**
- Need for computational efficiency since selection is performed thousand to million times during training
- Avoid exhaustive search

Random Forests - Node optimization

- Generate m split candidates
  $\rightarrow$ "Traditionally": $m = \sqrt{d}$, where d is data dimension
  $\rightarrow$ "Modern" approaches: $m \approx 10^5$
  $\rightarrow$ Usually even $m = 2$ leads to performance increase
  $\rightarrow$ Trade-off between high performance and high correlation
- Select best split, reject all others
- Measure optimality of a split
  - Classification: "Purity" of child nodes (e.g. Gini, entropy, etc.)
  - Regression: e.g. variance
  - In general: How much better is the estimation of the child nodes (as a weighted average) than parent nodes?

Random Forests - Node optimization



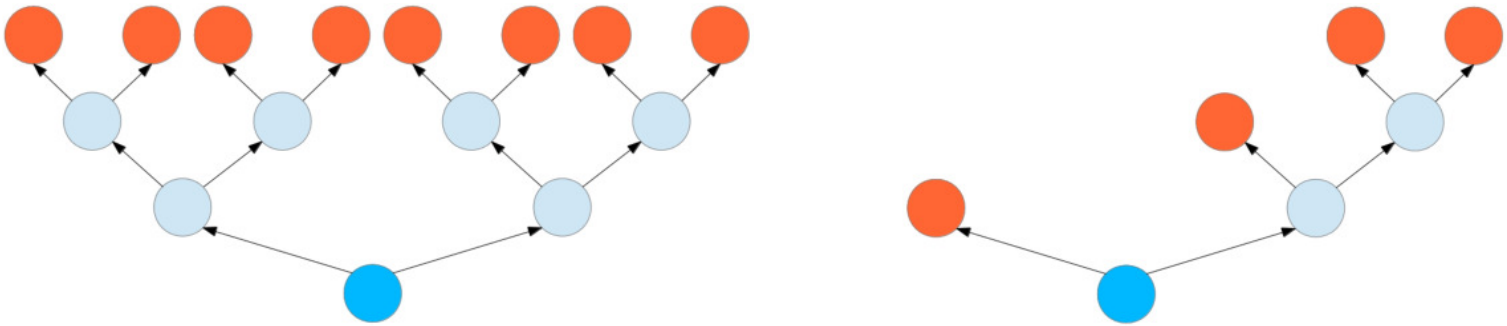
Random Forests - Node optimization

- Different energy functions allow simultaneous optimization of different targets
- Common example: Classification (Object class) **and** regression (Object position)
- e.g. **Hough Forests**[Gall et al., 2011]
  - Training Data: $D = \{P_i = (I_i, c_i, d_i)\}$
  - Randomly decide for one of two energy functions:
    Entropy of posterior: $U_1(A) = -|A| \cdot \sum_c P(c|A) log(P(c|A))$
    Variance of offset vectors: $U_2(A) = \sum_c \sum_{d \in D_c^A} ||d - \bar{d}_c^A||$
  - Select best test t according to
    $\arg\min_t(U_*(\{P_i|t=0\}) + U_*(\{P_i|t=1\}))$
  - Use offset vectors and class posterior to perform Hough voting during prediction

Random Forests - Structured prediction

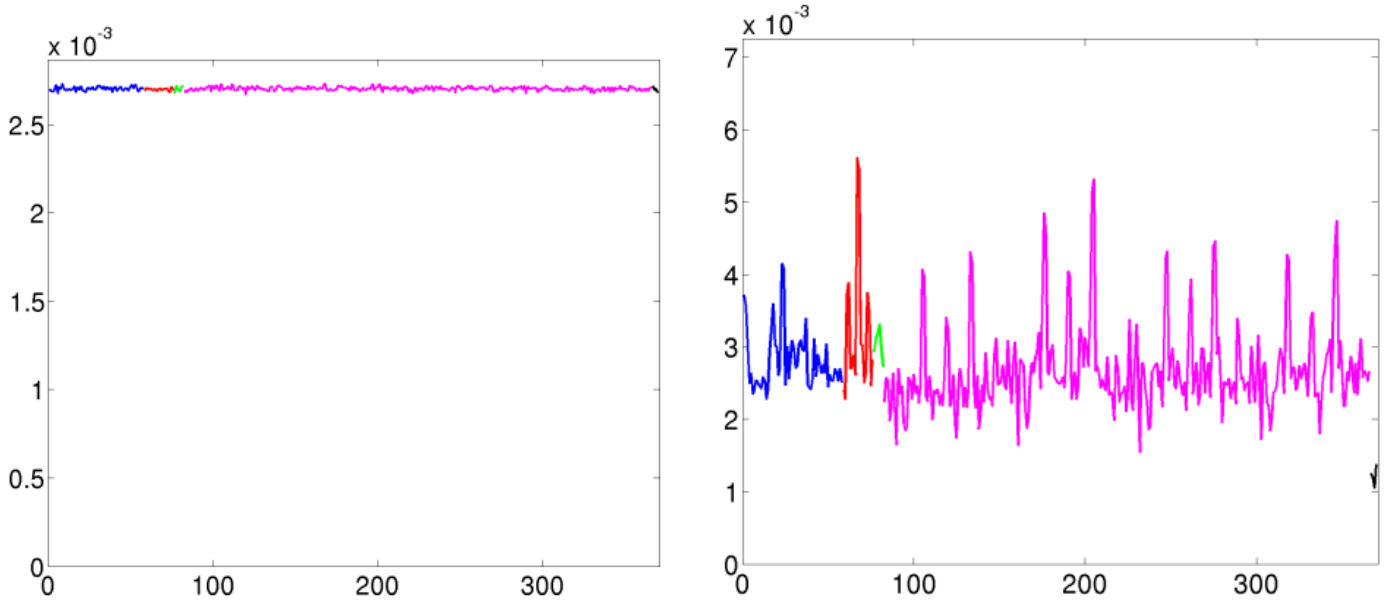
- Image data is structured
- Exploited already during structured projection within node tests
- Target variable can be structured as well
  $\rightarrow$ Offset vectors, label patch
- Enriched spatial estimate for image labeling
- Disadvantage: Increased memory footprint

Random Forests - Interpretation



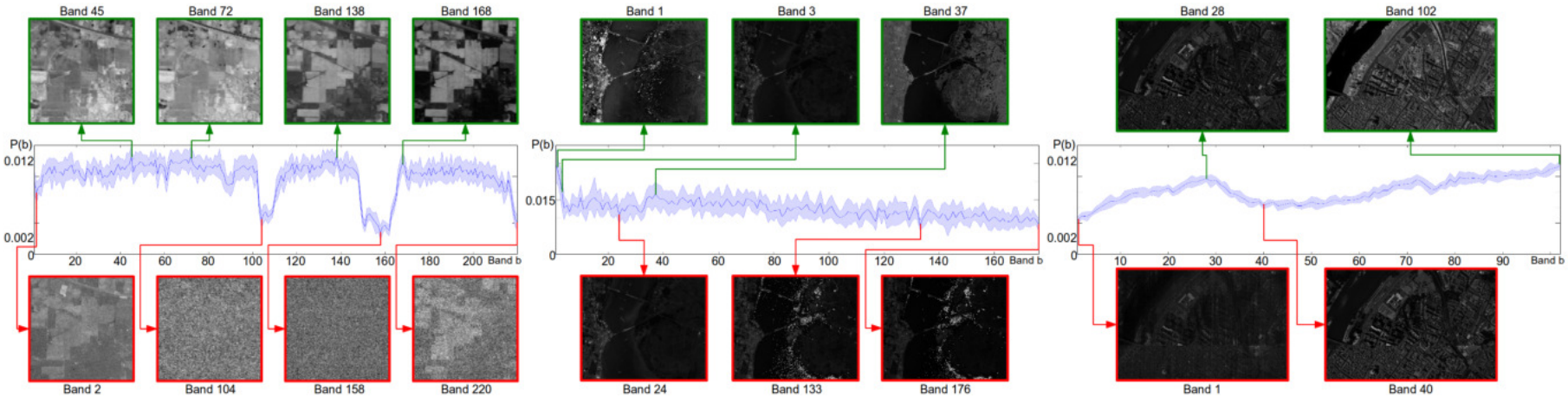
- Is maximum tree height reached?
- How balanced is a tree? $\frac{\#\text{nodes}}{2^{H+1}-1}$
- How large is largest leaf? $1 - \frac{\max_{n_t} |D_{n_t}|}{|D|}$
- How pure is largest leaf? $I(n^*)$ with $n^* = \arg\max_{n_t} |D_{n_t}|$
- Out-of-bag estimate for generalization error
- Out-of-bag estimate for correlation

Random Forests - Feature relevance



- RF for PolSAR image labeling, roughly 360 image features as input:
  (PolSAR-blue, SAR-red, color-green, grayscale-magenta, binary-black)
- Each feature has same probability to be used (as seen on the left)
- Each feature is actually selected by the RF with very unequal frequency (as seen on the right)
- Features that have been used often are more important / descriptive for the task at hand

Random Forests - Feature relevance



[R. Hänsch, 2015a]

- RF for hyperspectral image labeling, $>$ 200 spectral bands as input
- Each band has same probability to be used
- Each band is actually selected by the RF with very unequal frequency
- Bands that have been used often are more important / descriptive for the task at hand

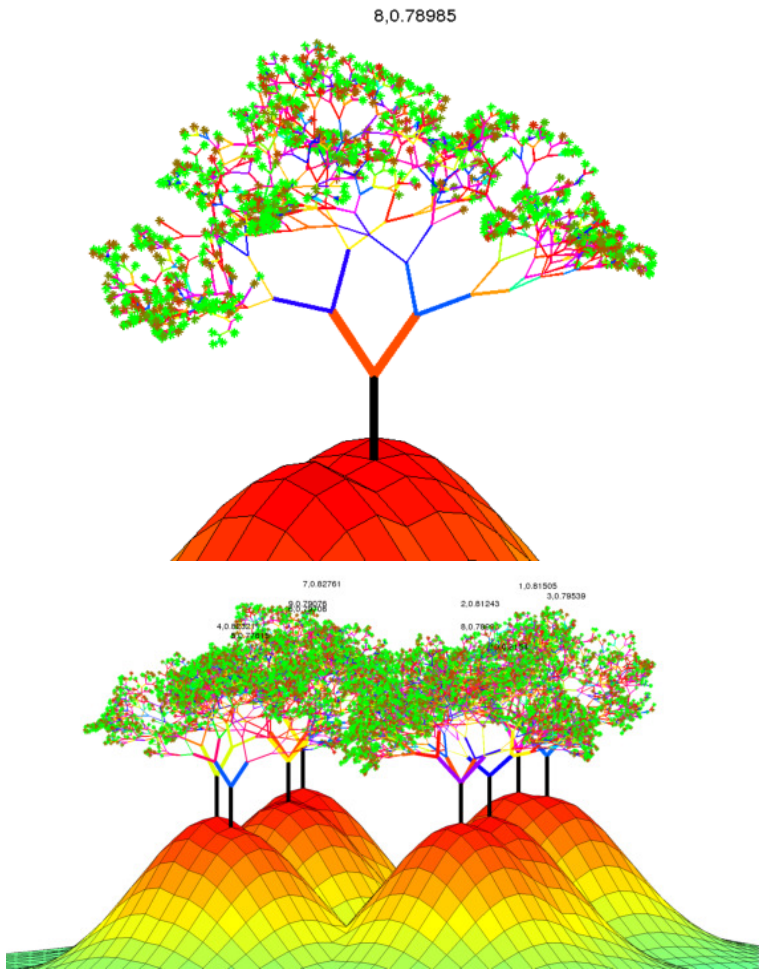
Random Forests - Visualization

Important Characteristics of a Random Forests

- Forest Level
  - Strength of the whole forest
    → e.g. classification accuracy
  - Correlation between trees
    → e.g. correlation of classification maps
- Tree Level
  - Strength of the individual tree
    → e.g. based on out-of-bag error
  - Structural layout of individual trees
    → e.g. balanced vs. degenerated chain
- Node Level
  - Node features
    → e.g. size, split dimension, drop of impurity, leaf impurity, etc.

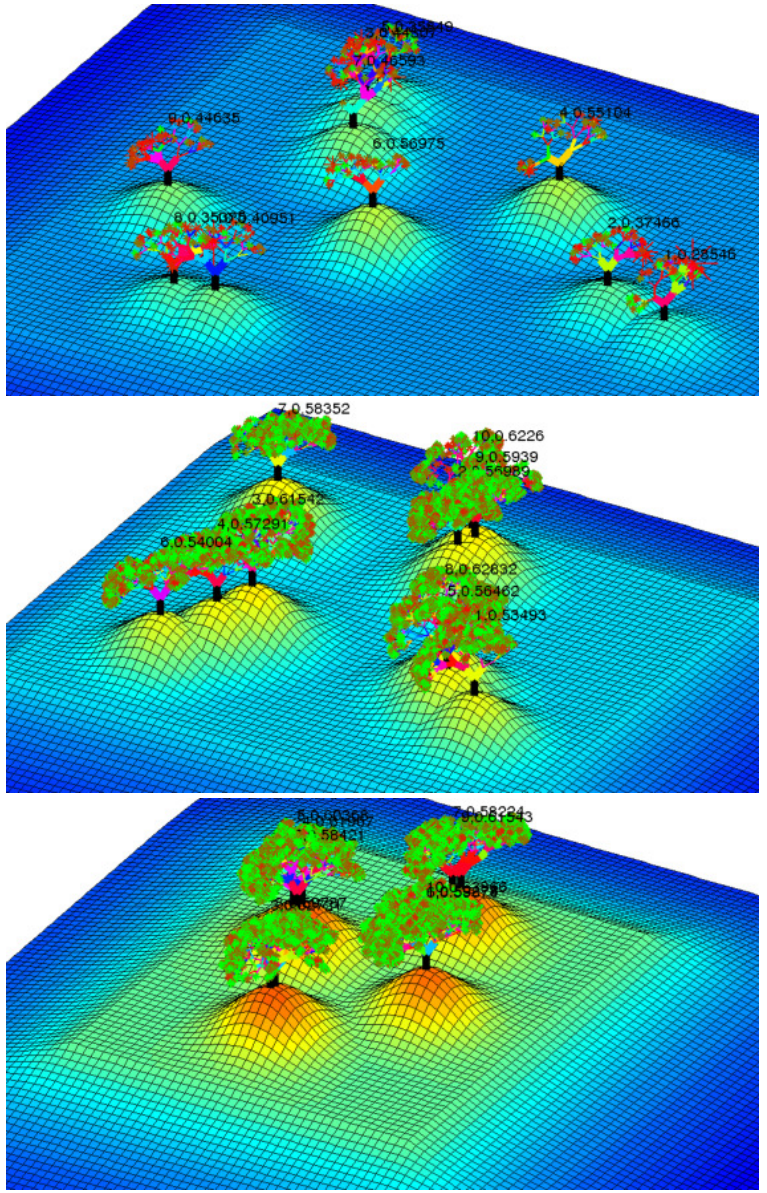
Random Forests - Visualization

- Branch
  - Color:
    (e.g.) split dimension
  - Thickness:
    Number of samples
  - Length:
    $l_{h+1}^{L/R} = l_h \cdot \kappa_2 \cdot ((f_{\text{max}} - f_{\text{min}}) + f_{\text{min}})$
  - Orientation:
    $(\alpha, \beta)_{h+1}^{L/R} = (\alpha, \beta)_h \pm (30°, \kappa_1 \cdot 45°)$
- Leaf
  - Color: Leaf impurity
  - Size: Leaf size
- 2D position
  Based on pairwise correlation



Random Forests - Visualization

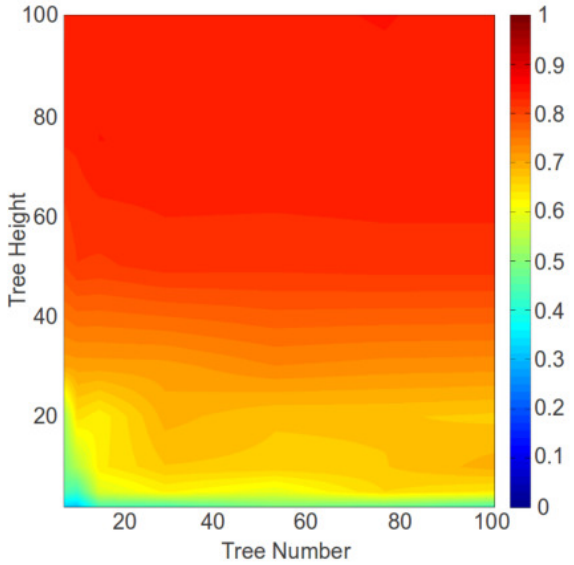
- Increasing tree height
- Trees getting higher
- Leafs getting purer
- Trees getting stronger
- Trees correlate stronger
- Forest gets stronger
- [R. Hänsch, 2015b]



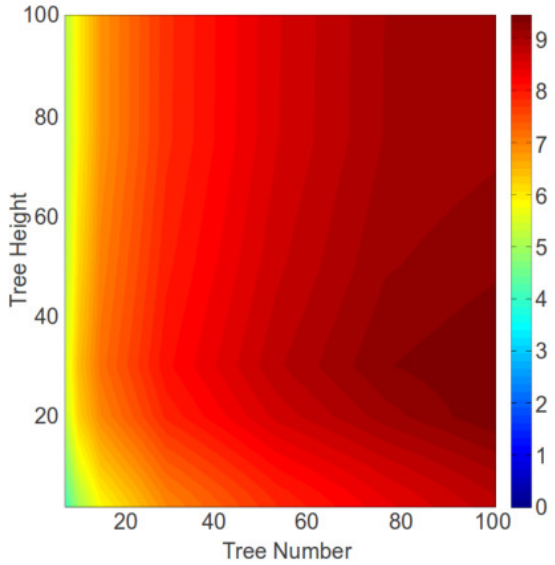
Random Forests - Practical Considerations

- Most implementations refer to standard RF (no spatial projections)
- Projection-based RF common in CV community (due to images!)
- GPU implementations available
- Many spatial projections can be approximated by integral images
- Not all data samples in a node have to be used to define / select split point
- Tree creation (i.e. development of tree topology) can be performed independently from tree training (i.e. assign estimates to leaf nodes)
  $\rightarrow$ Only tree creation needs multiple data samples in memory.
  $\rightarrow$ Tree training can be done one sample after another
  $\rightarrow$ Online training for RF

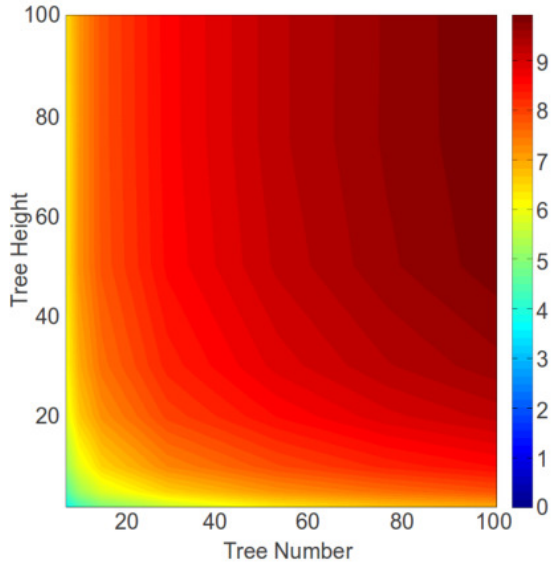
Random Forests - Best Practice



Accuracy



log-Training time

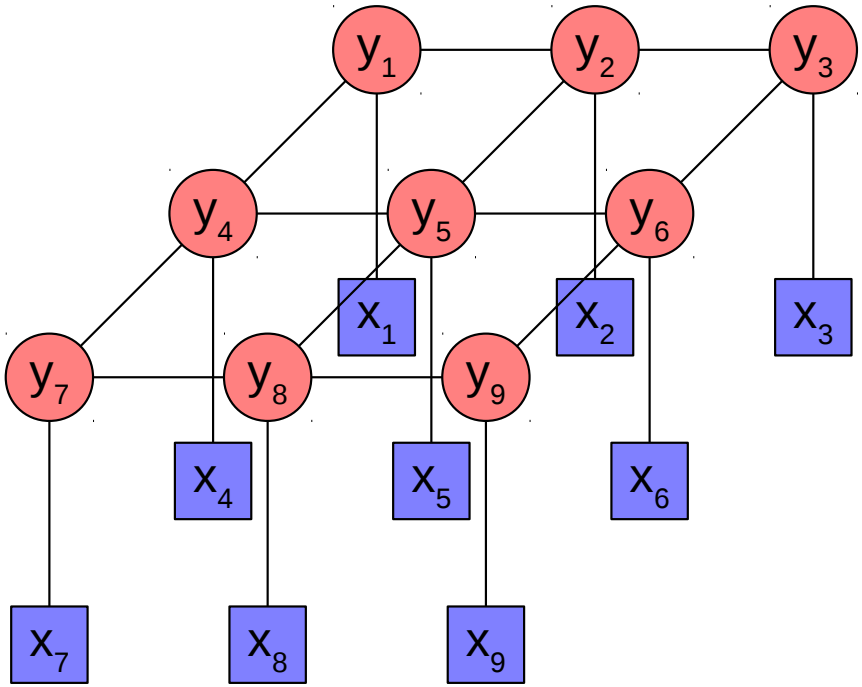


log-Prediction time

- Accuracy usually grows faster with tree height than tree number
- But: Tree height limited by amount of training data
- Use projections / features that are as diverse as possible
- Use simple split point definitions in combination with node optimization (i.e. selection)
- Check tree properties / visualize

Overview

1. Random Forests
   - Fusion
   - Node Tests
   - Interpretation
   - Application Tips
2. Graphical Models
   - Motivation
   - MRF
   - Application
   - Example
3. ConvNets
   - MLP to ConvNet
   - Convolution
   - Architectures
   - Auto Encoder
   - Frameworks



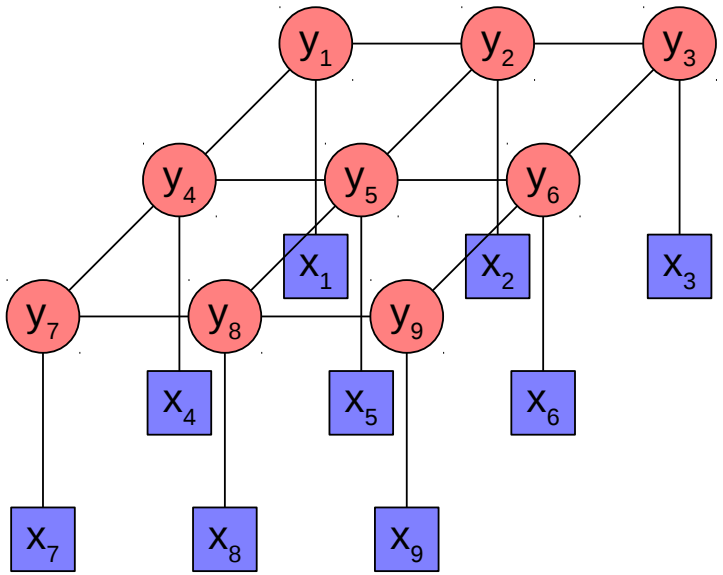
MRF

The same probabilistic model (e.g. for image labeling) as

mathematical equation

$$
\begin{aligned}
p(\mathbf{x},\mathbf{y}) \quad = \quad & p(y_3,x_3)p(y_5,y_6)p(y_8,y_9) \\
& p(y_8,x_8)p(y_9,x_9)p(y_3,y_6) \\
& p(y_6,y_9)p(y_1,x_1)p(y_2,y_5) \\
& p(y_4,y_7)p(y_4,y_5)p(y_6,x_6) \\
& p(y_2,x_2)p(y_5,y_8)p(y_7,x_7) \\
& p(y_2,y_3)p(y_1,y_4)p(y_5,x_5) \\
& p(y_1,y_2)p(y_4,x_4)p(y_7,y_8)
\end{aligned}
$$

graphical model



MRF

The same probabilistic model (e.g. for image labelling) as

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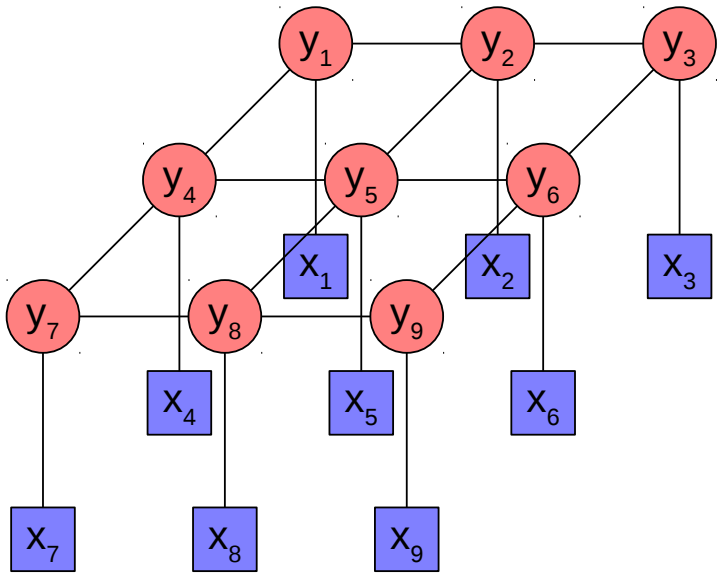
$$
\begin{aligned}
p(\mathbf{x}, \mathbf{y}) \quad = \quad & p(y_3, x_3)p(y_5, y_6)p(y_8, y_9) \\
& p(y_8, x_8)p(y_9, x_9)p(y_3, y_6) \\
& p(y_6, y_9)p(y_1, x_1)p(y_2, y_5) \\
& p(y_4, y_7)p(y_4, y_5)p(y_6, x_6) \\
& p(y_2, x_2)p(y_5, y_8)p(y_7, x_7) \\
& p(y_2, y_3)p(y_1, y_4)p(y_5, x_5) \\
& p(y_1, y_2)p(y_4, x_4)p(y_7, y_8)
\end{aligned}
$$

graphical model

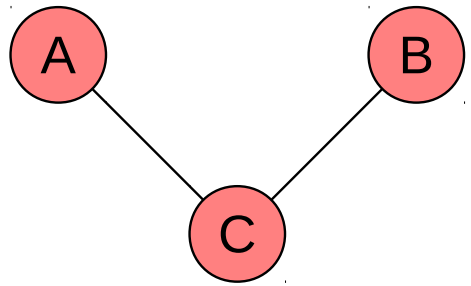


- Dependencies visually recognizable
- Different types of nodes
- Scales easily to larger models (if there are no structural changes)

MRF - Conditional Independence

Events A and B are conditional independent given event C: $A \perp B|C$

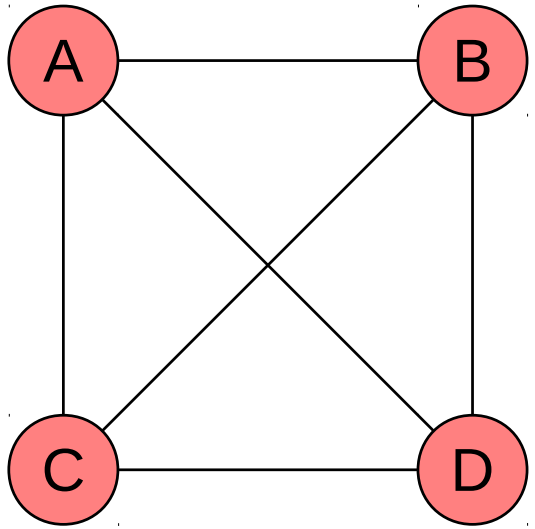
$$
\begin{aligned}
P(A, B|C) &= P(A|C) \cdot P(B|C) \\
P(A|B, C) &= P(A|C) \\
P(B|A, C) &= P(B|C)
\end{aligned}
$$



- My blood type $\perp$ Blood type of grandparents | Blood type of parents
- Weather tomorrow $\perp$ Weather yesterday | Weather today
- Value of a pixel $\perp$ Value of pixels far away | Value of adjacent pixels

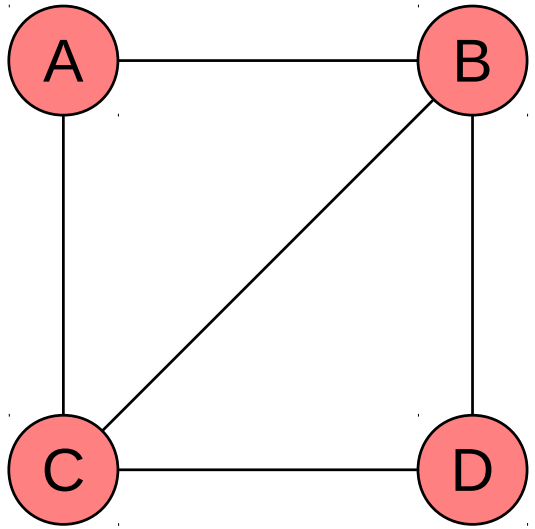
MRF - Conditional Independence

$$
\begin{aligned}
P(A,B,C,D) &= P(A|B,C,D) \\
&\cdot P(B|C,D) \\
&\cdot P(C|D) \\
&\cdot P(D)
\end{aligned}
$$



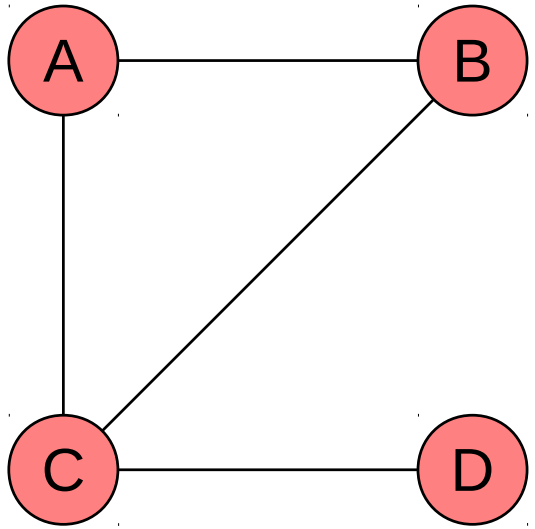
MRF - Conditional Independence

$$
\begin{aligned}
A \perp D \quad &| \quad C, B \\
P(A,B,C,D) \quad &= \quad P(A|B,C) \\
&\quad \cdot P(B|C,D) \\
&\quad \cdot P(C|D) \\
&\quad \cdot P(D)
\end{aligned}
$$



MRF - Conditional Independence

$$
\begin{aligned}
A \perp D \quad &| \quad C, B \\
B \perp D \quad &| \quad C \\
P(A, B, C, D) \quad &= \quad P(A|B, C) \\
&\quad \cdot P(B|C) \\
&\quad \cdot P(C|D) \\
&\quad \cdot P(D)
\end{aligned}
$$



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$$
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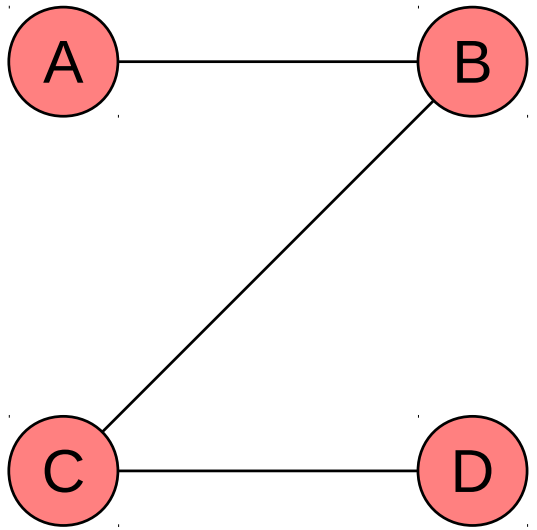
A \perp D \quad &| \quad C, B \\
B \perp D \quad &| \quad C \\
A \perp C \quad &| \quad B \\
P(A,B,C,D) \quad &= \quad P(A|B) \\
&\quad \cdot P(B|C) \\
&\quad \cdot P(C|D) \\
&\quad \cdot P(D)
\end{aligned}
$$



MRF - Conditional Independence

$$
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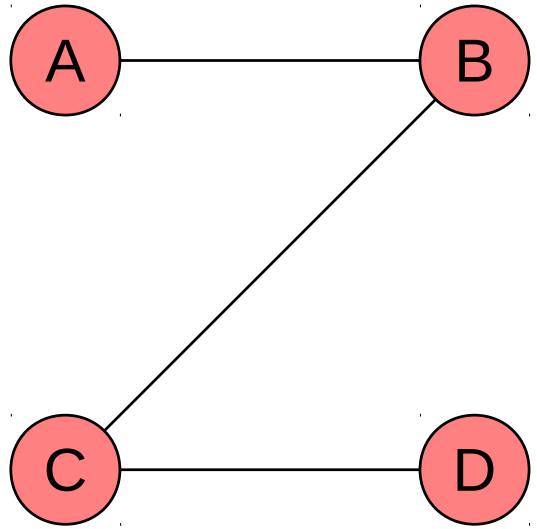
A \perp D \quad &| \quad C, B \\
B \perp D \quad &| \quad C \\
A \perp C \quad &| \quad B \\
P(A,B,C,D) \quad &= \quad P(A|B) \\
&\quad \cdot P(B|C) \\
&\quad \cdot P(C|D) \\
&\quad \cdot P(D)
\end{aligned}
$$

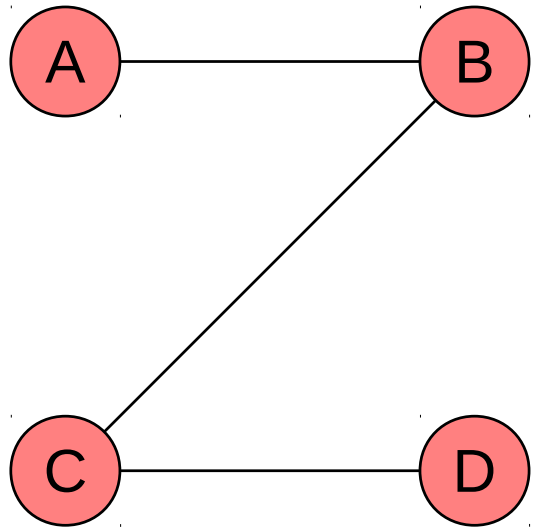


Marginalization: $P(A) = \sum_B \sum_C \sum_D P(A,B,C,D)$

$\rightarrow |A| \cdot |B| \cdot |C| \cdot |D|$ operations

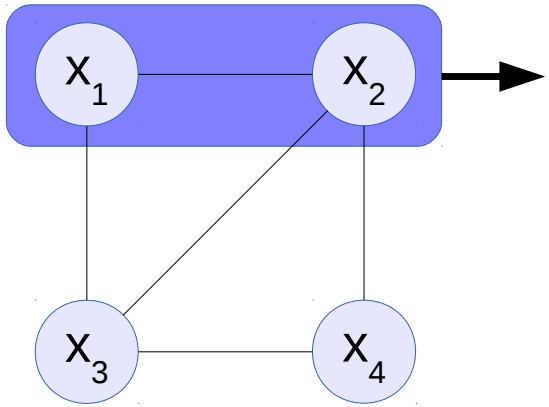
MRF - Conditional Independence

$$
\begin{aligned}
A \perp D \quad &| \quad C, B \\
B \perp D \quad &| \quad C \\
A \perp C \quad &| \quad B \\
P(A,B,C,D) \quad &= \quad P(A|B) \\
&\quad \cdot P(B|C) \\
&\quad \cdot P(C|D) \\
&\quad \cdot P(D)
\end{aligned}
$$



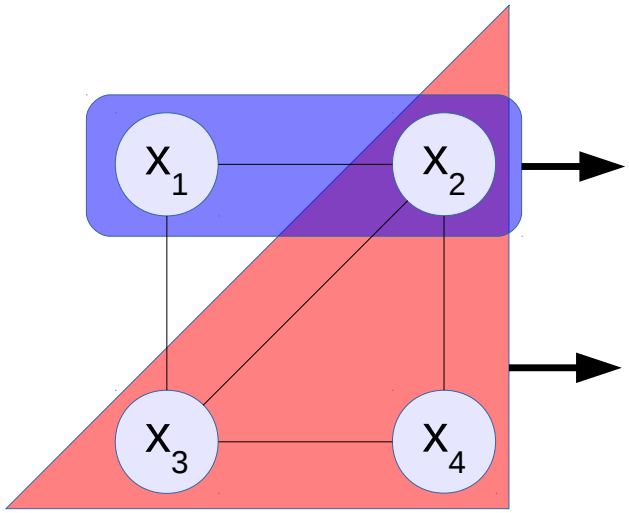
$$
\begin{aligned}
\text{Marginalization: } P(A) &= \sum_B \sum_C \sum_D P(A|B) \cdot P(B|C) \cdot P(C|D) \cdot P(D) \\
&= \sum_B P(A|B) \cdot \sum_C P(B|C) \cdot \sum_D P(C|D) \cdot P(D) \\
&\rightarrow |A| \cdot (|B| + |C| + |D|) \text{ operations}
\end{aligned}
$$

MRF - Notation



Clique: Complete subgraph
→ all pairs of nodes connected

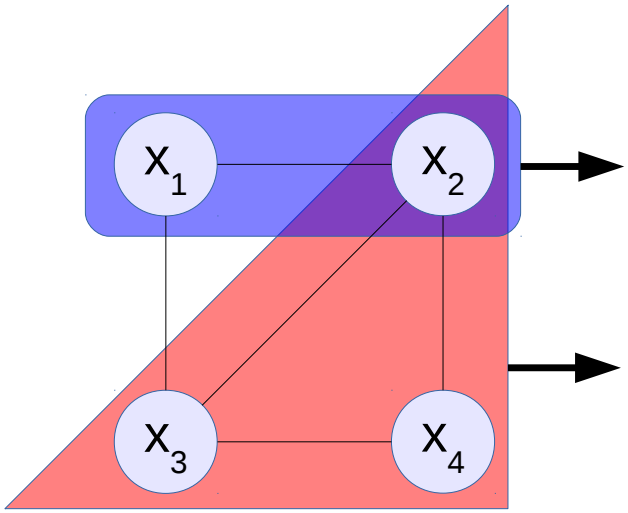
MRF - Notation



Clique: Complete subgraph
→ all pairs of nodes connected

Maximal Clique:
→ No subset of any other clique

MRF - Notation



Clique: Complete subgraph
→ all pairs of nodes connected

Maximal Clique:
→ No subset of any other clique

$$p(\mathbf{x}) = \frac{1}{Z} \prod_{c \in C} \Psi_c(\mathbf{x}_c)$$

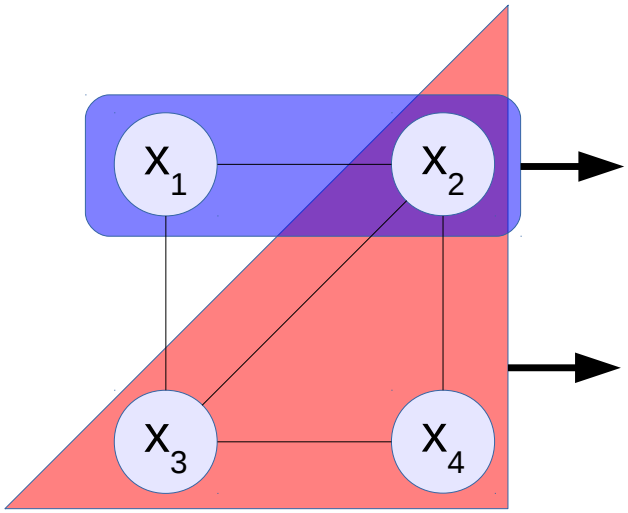
C : Set of maximal cliques

$\mathbf{x}_c$: Nodes in clique c

$\Psi(\cdot)$: Non-negative real-valued function, e.g. $\exp(\psi(\mathbf{x}_c))$

Z : Normalization such that $\int p(\mathbf{x}) d\mathbf{x} = 1$

MRF - Notation

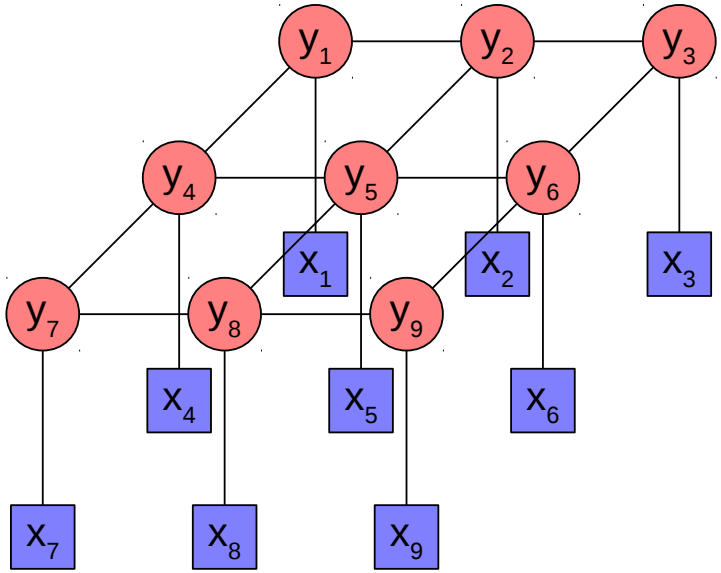


Clique: Complete subgraph
→ all pairs of nodes connected

Maximal Clique:
→ No subset of any other clique

$$
\begin{aligned}
p(\mathbf{x}) &= \frac{1}{Z} \prod_{c \in C} \Psi_c(\mathbf{x}_c) \\
&= \frac{1}{Z} \prod_{c \in C} \exp(\psi_c(\mathbf{x}_c)) \\
&= \frac{1}{Z} \exp\left(\sum_{c \in C} \psi_c(\mathbf{x}_c) \right) = \frac{1}{Z} \exp(-E(\mathbf{x}))
\end{aligned}
$$

MRF - Notation

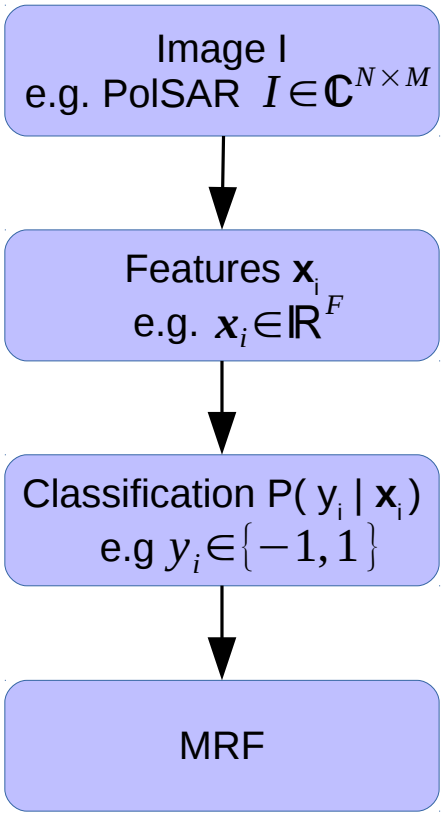


$$p(\mathbf{x},\mathbf{y}) = \frac{1}{Z}\prod_{c\in C}\Psi_c(\mathbf{x}_c,\mathbf{y}_c) = \frac{1}{Z}\exp(-E(\mathbf{x},\mathbf{y}))$$

$$E(\mathbf{x},\mathbf{y}) = \sum_{y_i}\underbrace{\psi^U(y_i,x_i)}_{\text{Unary energy}} + \sum_{y_i,y_j}\underbrace{\psi^B(y_i,y_j)}_{\text{Binary energy}} + \sum_{c\in C}\underbrace{\psi^H(\mathbf{y}_c,\mathbf{x}_c)}_{\text{Higher-order energy}}$$

MRF - Simple Example

Binary classification task
MRF used for simple label smoothing

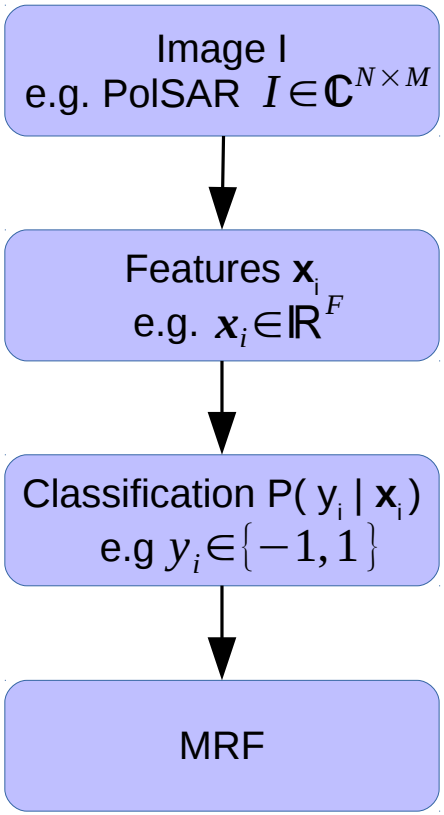


$$\psi^U(y_i, x_i) = -\log P(y_i|x_i)$$
$$\psi^B(y_i, y_j) = -y_i \cdot y_j$$

MRF - Simple Example

Binary classification task

MRF with contrast-dependent smoothness prior



$$\psi^U(y_i, x_i) = -\log P(y_i|x_i)$$

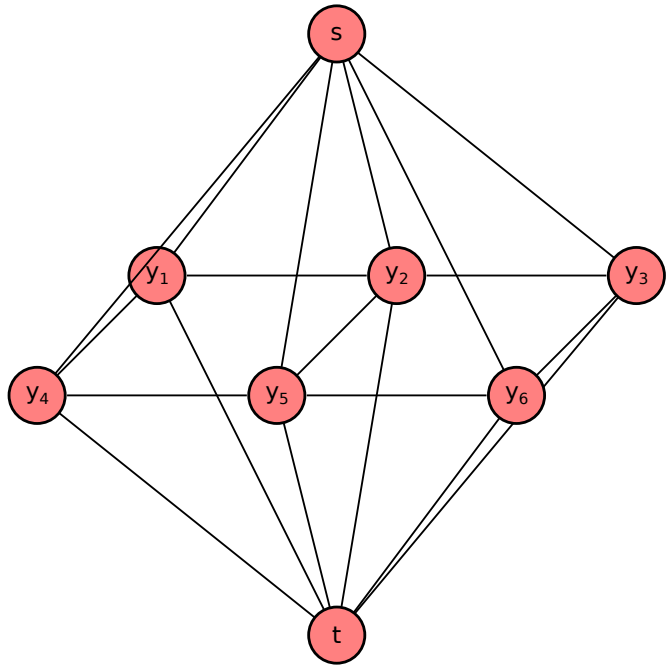
$$\psi^B(y_i, y_j) = \begin{cases} \lambda_0 + \lambda_1 e^{\left(-\frac{||x_i - x_j||^2}{2\beta}\right)} & \text{if } y_i \neq y_j \\ 0 & \text{otherwise.} \end{cases}$$

Graph Cut

- Given all $\mathbf{x}$, what are the most probable $\mathbf{y}$?
- Which $\mathbf{y}$ minimizes $E(\mathbf{x}, \mathbf{y}) = \sum_{y_i} \psi^U(y_i, x_i) + \sum_{y_i, y_j} \psi^B(y_i, y_j)$?

Graph Cut

- Given all **x**, what are the most probable **y**?
- Which **y** minimizes $E(\mathbf{x}, \mathbf{y}) = \sum_{y_i} \psi^U(y_i, x_i) + \sum_{y_i, y_j} \psi^B(y_i, y_j)$?
- Build a new graph with source and sink
- Binary potentials as weights between pixels
- Unary potentials als weights towards source/sink



Graph Cut

- Given all **x**, what are the most probable **y**?
- Which **y** minimizes $E(\mathbf{x}, \mathbf{y}) = \sum_{y_i} \psi^U(y_i, x_i) + \sum_{y_i, y_j} \psi^B(y_i, y_j)$?
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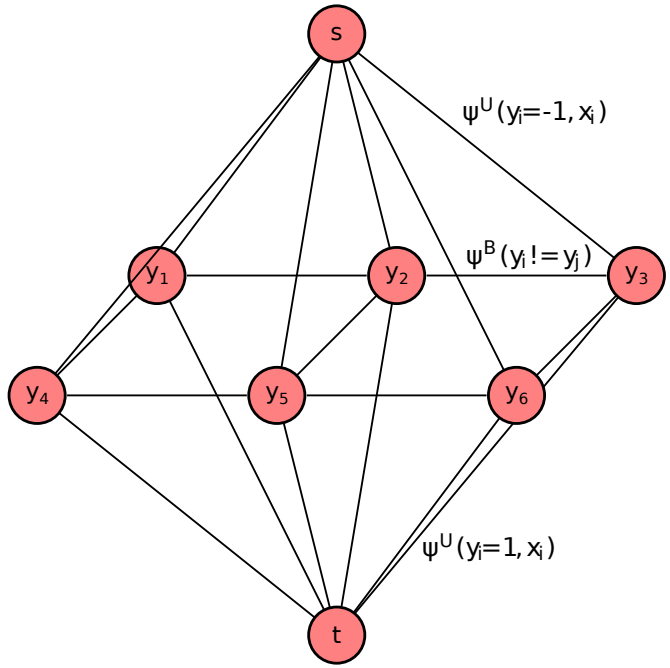
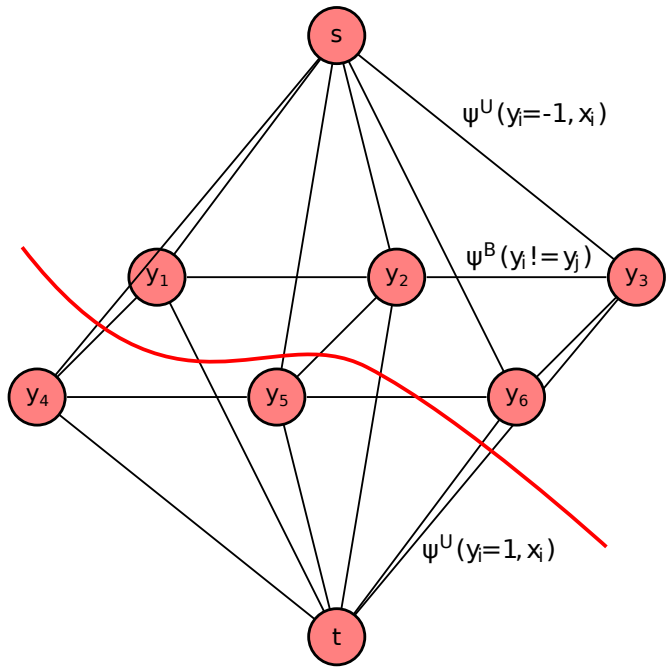


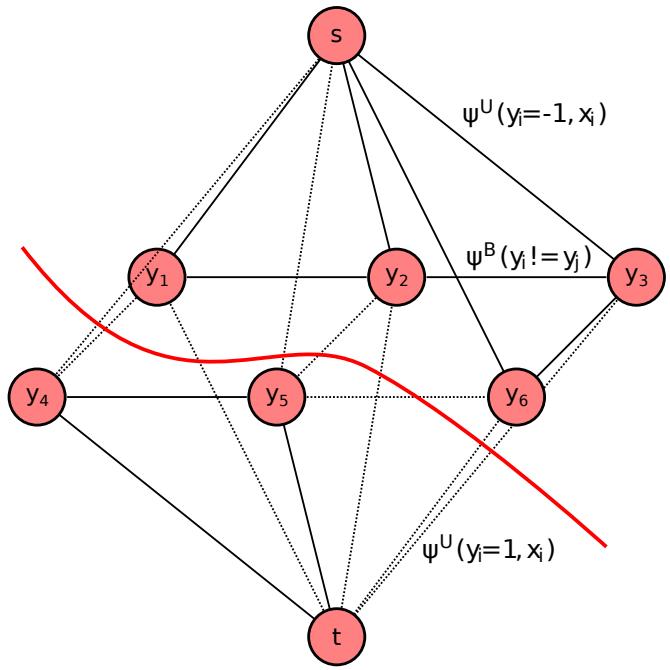
Graph Cut

- Min-Cut:
  - Cut that separates source and sink
  - Sum of cut edges (their weight) minimal
- This gives labeling of lowest MRF energy!
- Computing Min-Cut standard problem with lots of implementations



Graph Cut

- Min-Cut:
  - Cut that separates source and sink
  - Sum of cut edges (their weight) minimal
- This gives labeling of lowest MRF energy!
- Computing Min-Cut standard problem with lots of implementations



Non-Binary Classification

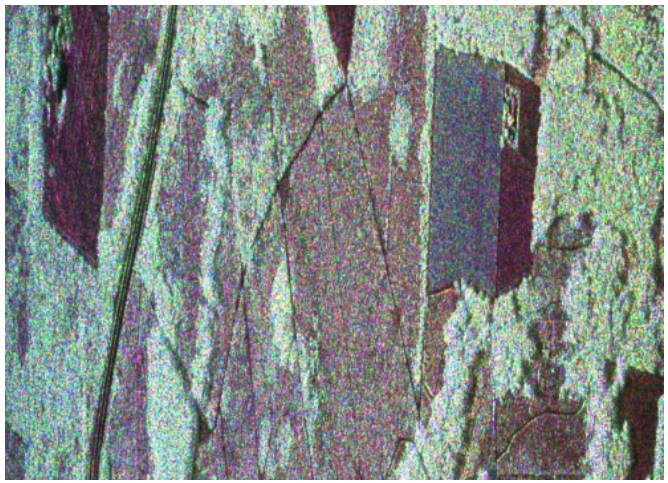
- What about non-binary, multi class problems?

Non-Binary Classification

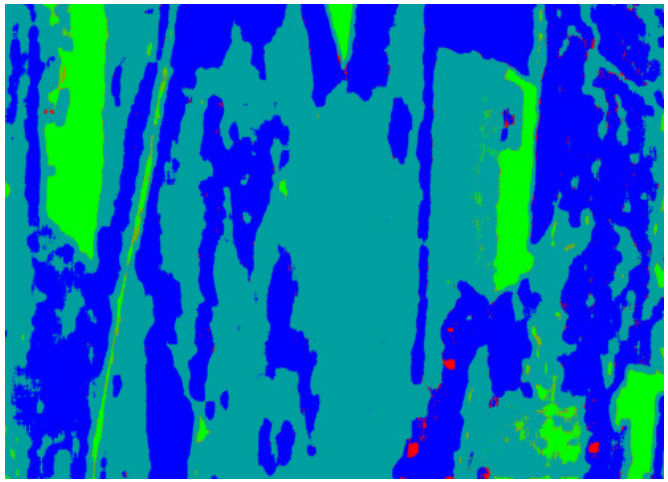
- What about non-binary, multi class problems?
- Approximate solution: Alpha-Expansion [Boykov et al., 2001]
- Loop over all labels
- For each label, allow region expansion based on graph cut
- Make multiple passes
- Graph slightly different

MRF - Alpha Expansion

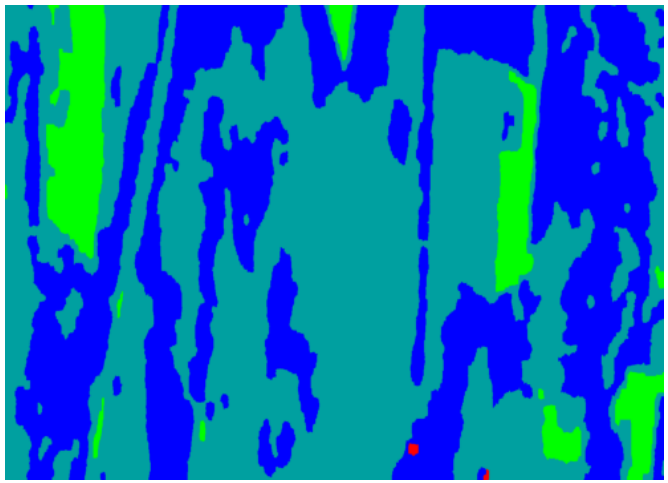
- Extract standard PolSAR features (span, entropy, anisotropy, etc.)
- First prediction by kNN
- Label smoothing by MRF + Alpha expansion



Original data



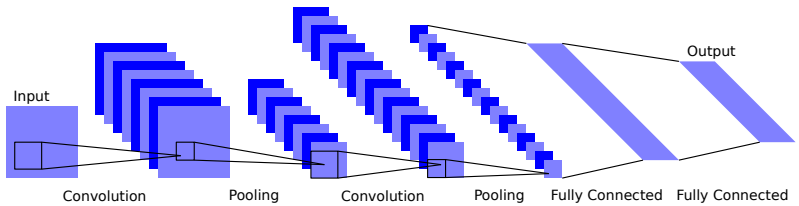
Initial estimate



After label smoothing

Overview

1. Random Forests
   - Fusion
   - Node Tests
   - Interpretation
   - Application Tips
2. Graphical Models
   - Motivation
   - MRF
   - Application
   - Example
3. ConvNets
   - MLP to ConvNet
   - Convolution
   - Architectures
   - Auto Encoder
   - Frameworks



Recap MLP

MLPs

- Provide a mapping from $\mathcal{X} \rightarrow \mathcal{Y}$, i.e. from a features space (usually $\mathcal{X} \equiv \mathbb{R}^n$) to a label space $\mathcal{Y}$
- Are based on concatenation of "simple" functions that depend on parameters (i.e. weights)
- Are optimized by gradient descent (and its modern extensions)

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- Are based on concatenation of "simple" functions that depend on parameters (i.e. weights)
- Are optimized by gradient descent (and its modern extensions)
- Work great, BUT:

ConvNets and Deep Learning

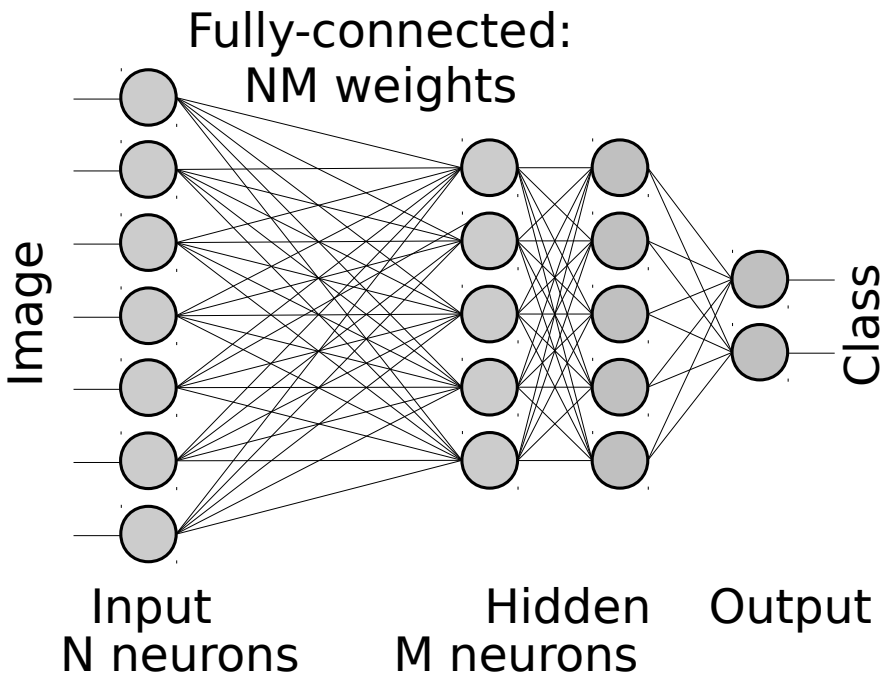
- Used by
  - Facebook: Automatic tagging
  - Google: Photo search
  - Amazon: Recommendations
  - Pinterest: Home feed personalization
  - Instagram: Search
- Buzzwords
  - Deep Learning, Deep Networks
  - Convolutional Neural Networks (CNNs), Convolutional Networks (ConvNets)
  - Note: There are more Deep Networks / Deep Learning approaches than ConvNets

ConvNets and Deep Learning

"CNNs are inspired by biological principles in the visual cortex."

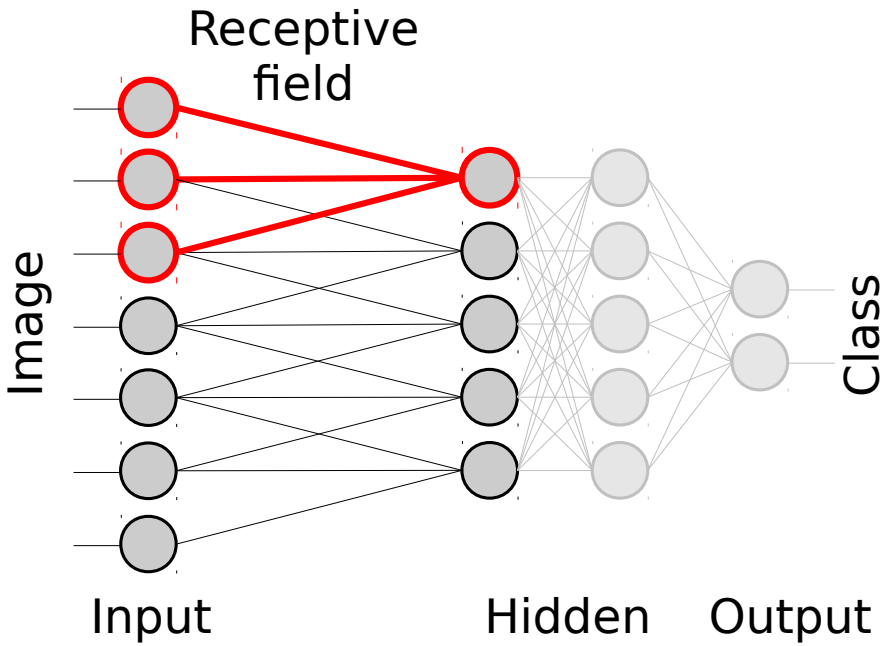
- Small regions of cells sensitive to specific regions within the visual field.
- 1962, Hubel and Wiesel
  - Neuronal cells fire only in the presence of certain structures e.g. edges of a specific orientation
  - Organized in columns
- Good selling point, BUT:
  - Extracting image features is neither new, nor the main point of ConvNets
  - Training works very differently

From FullyConnected (MLP) to Convolution (ConvNet)



- Multiple layers of units
- All-to-all connection between two adjacent layers
- No lateral connections
- A tremendous amount of parameters in case of images
  $\rightarrow$ Untrainable

From FullyConnected (MLP) to Convolution (ConvNet)



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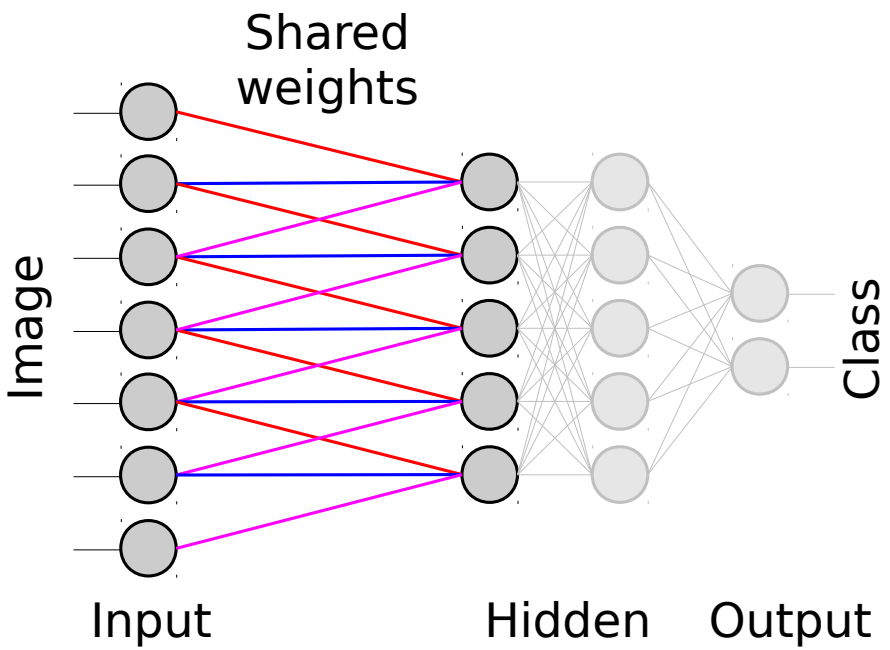

- Set most weights to zero and thus delete most connections and decrease parameters.
- Use same values for weights of different neurons within a layer.
- The multiplication of the input with identical weights for different neurons corresponds to a convolution.
- The kernel of this convolution is automatically learned.

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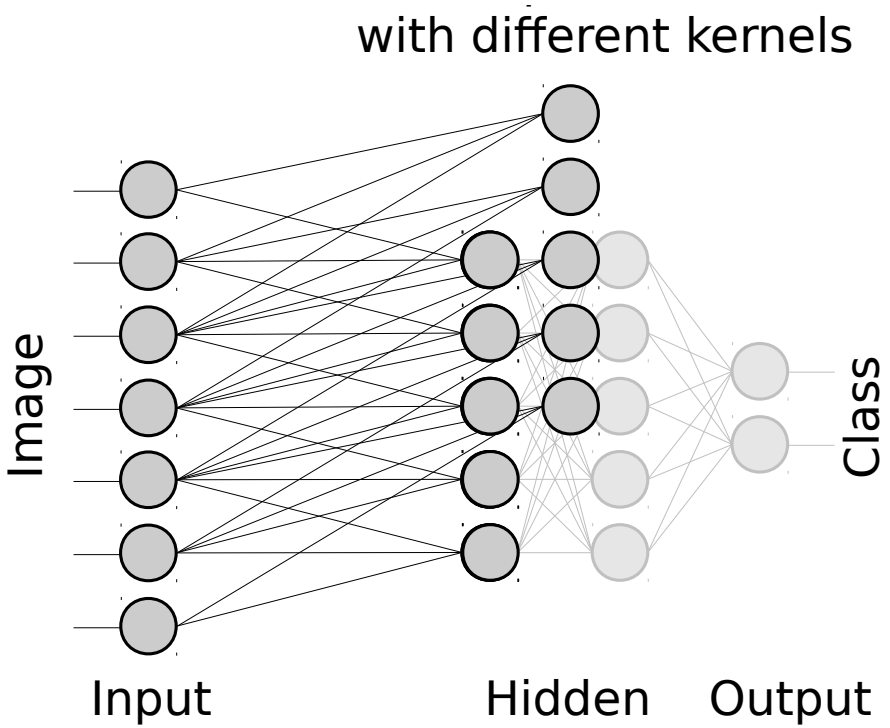

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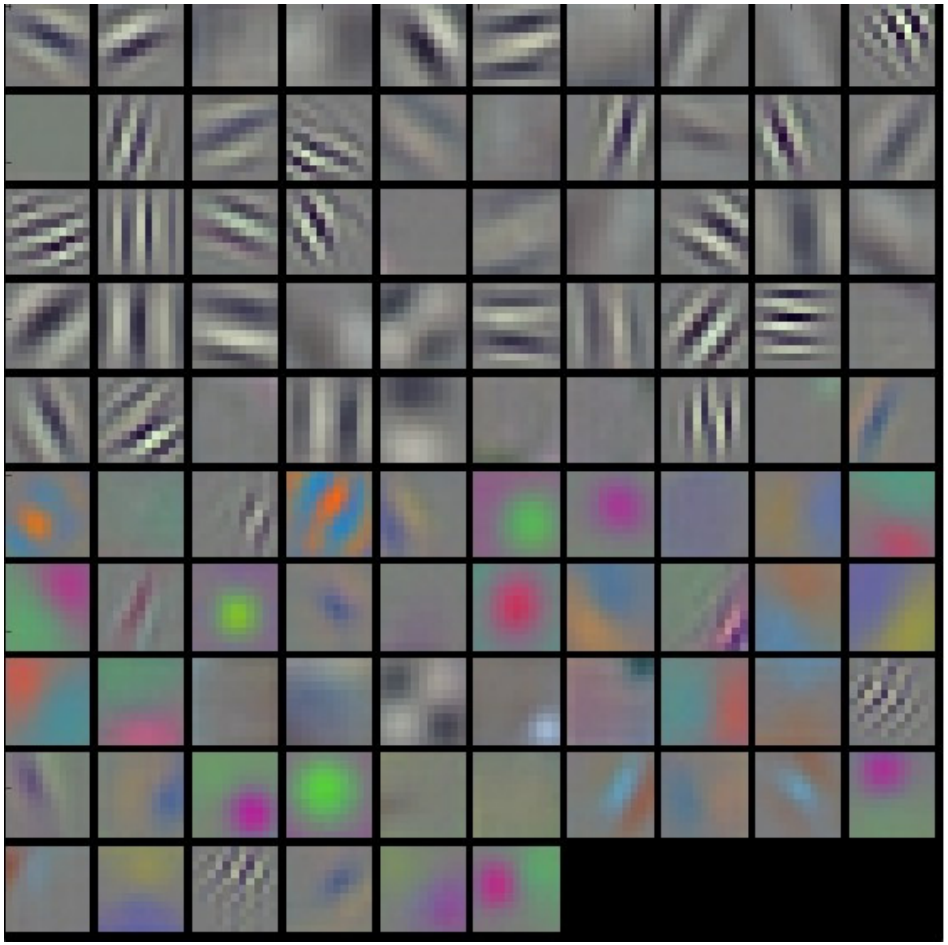
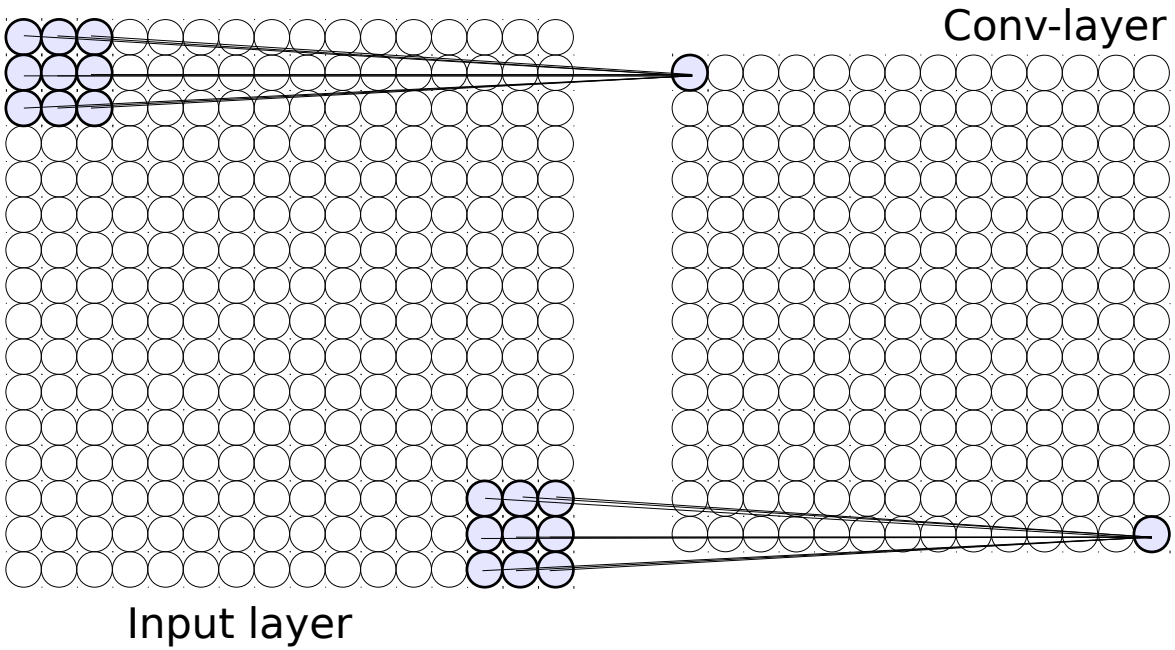
- Use same values for weights of different neurons within a layer.
- The multiplication of the input with identical weights for different neurons corresponds to a convolution.
- The kernel of this convolution is automatically learned.
- Use multiple convolutional layers to enable different kernels to be learned.

Example of First Level Filters

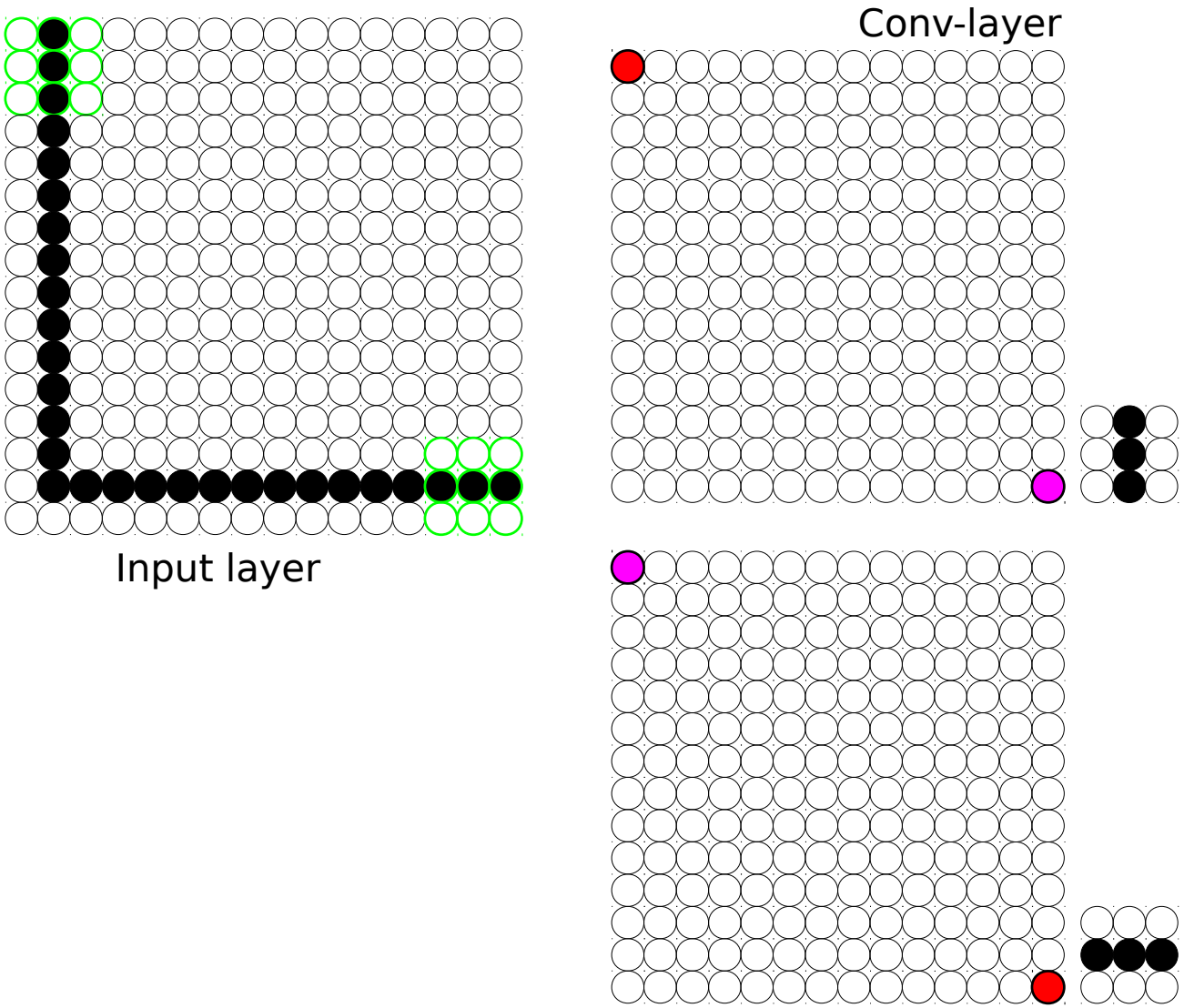


- Learned kernels of first convolutional layer of a ConvNet (AlexNet).
- Correspond mostly to edges and corners of different orientations.
- Note: Grouping is caused by network architecture (two independent streams were used to handle the large amount of data).

Pooling



Pooling



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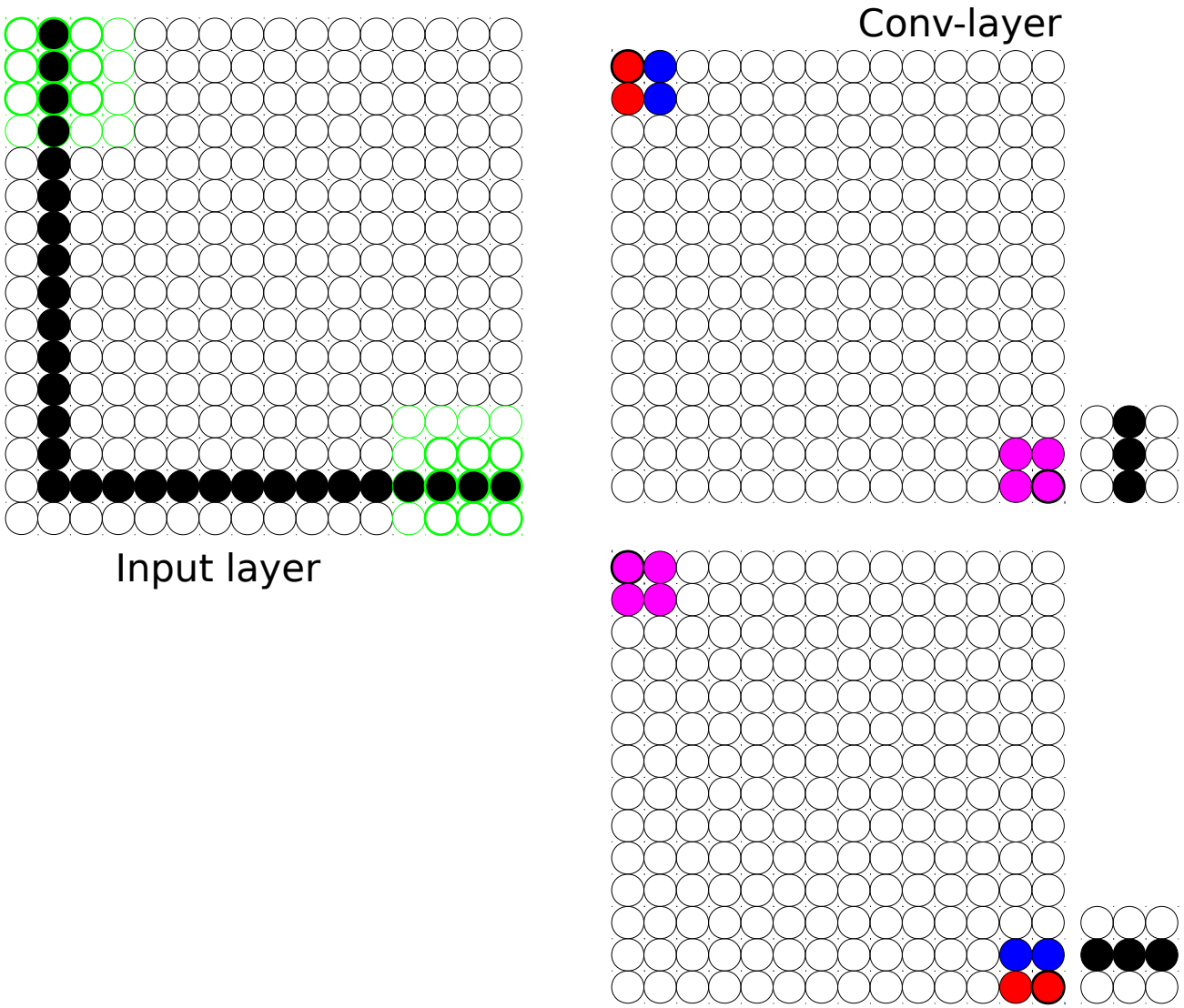

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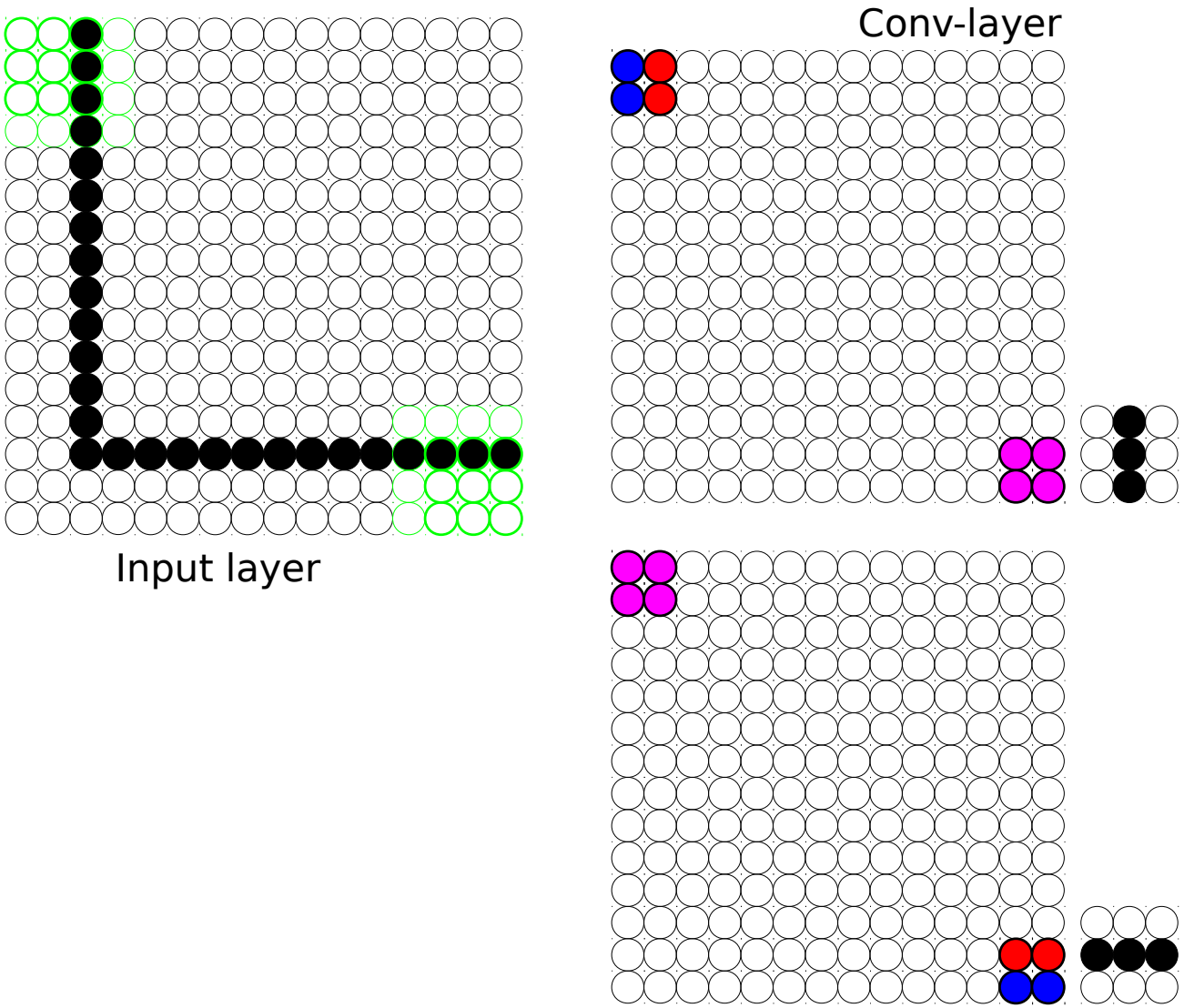

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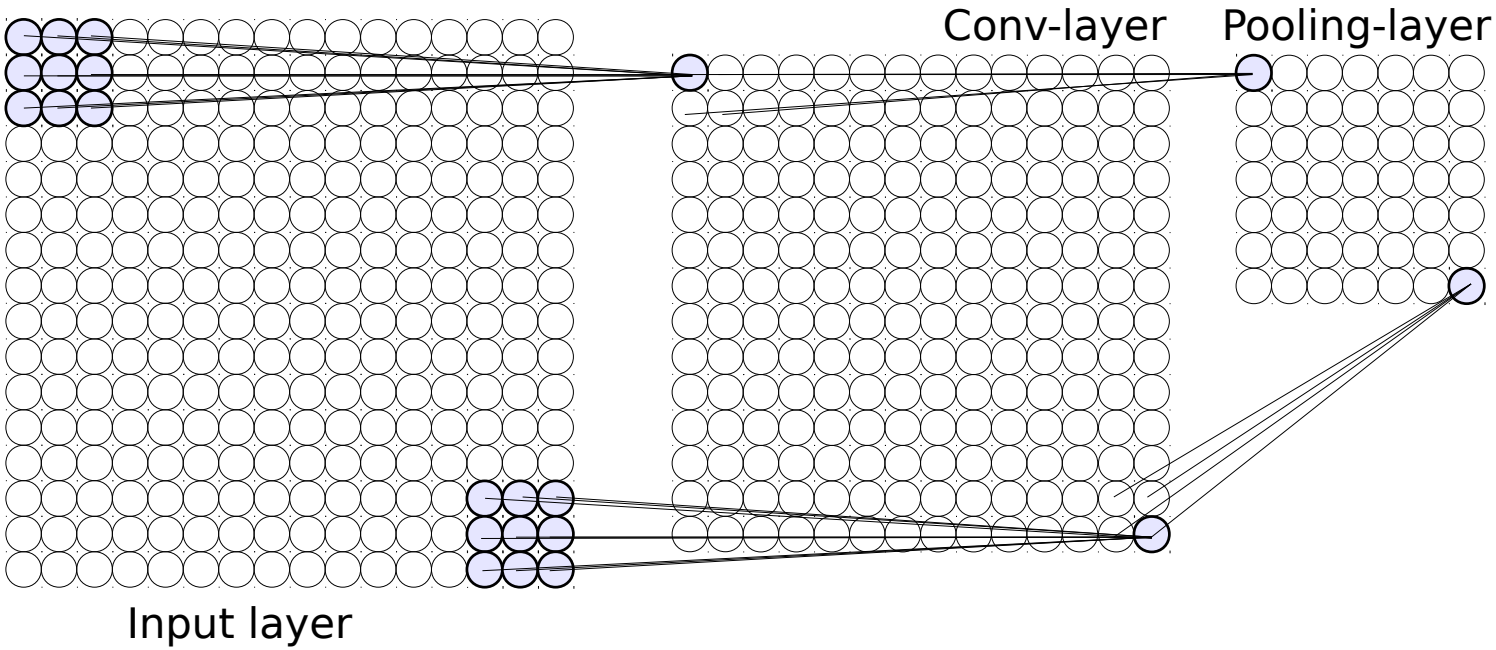

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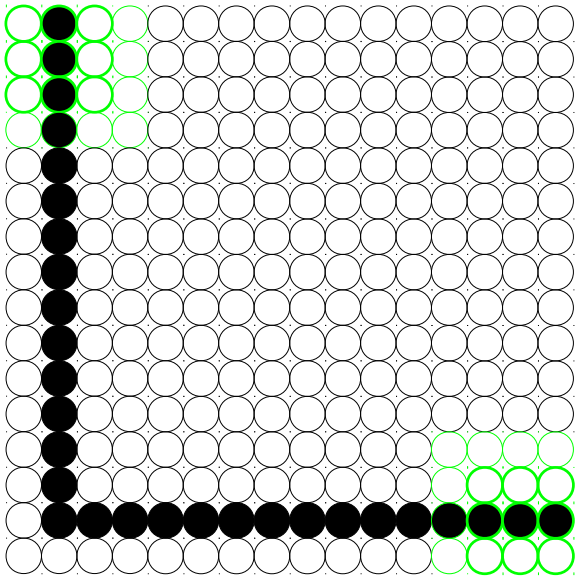
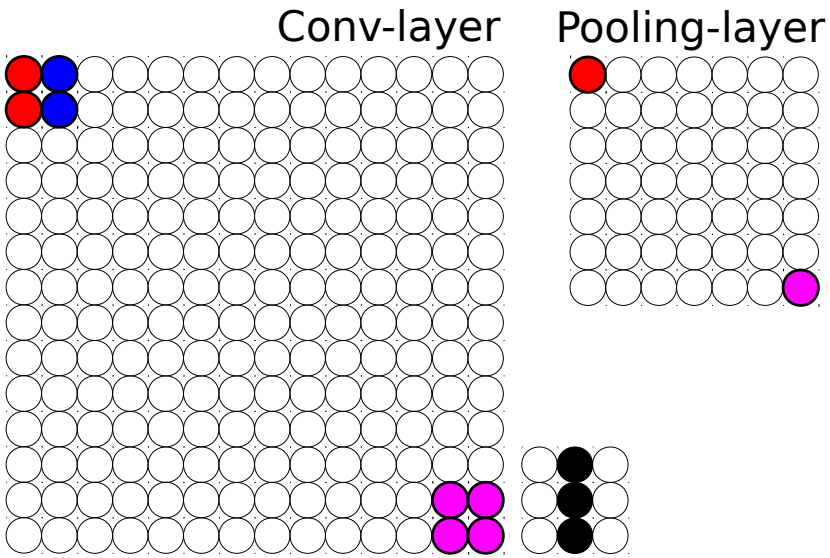
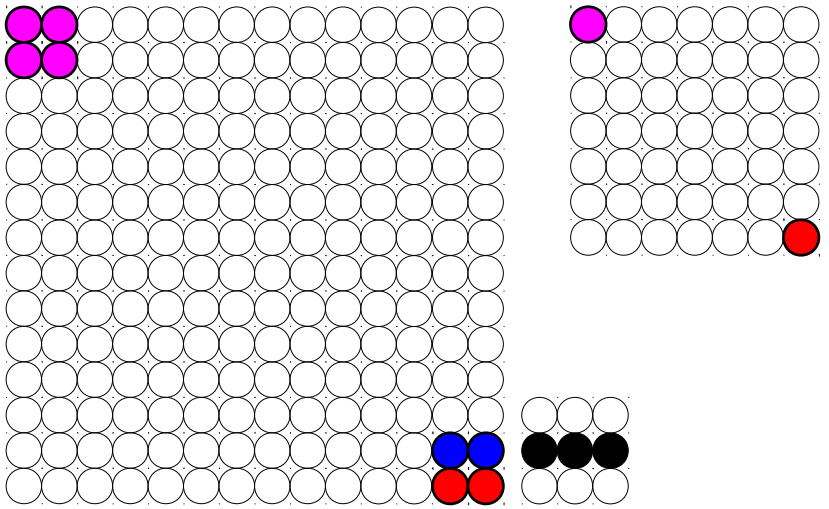


Input layer





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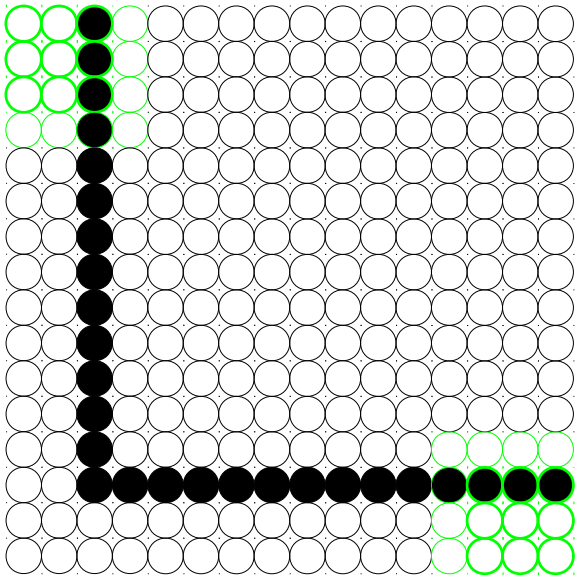

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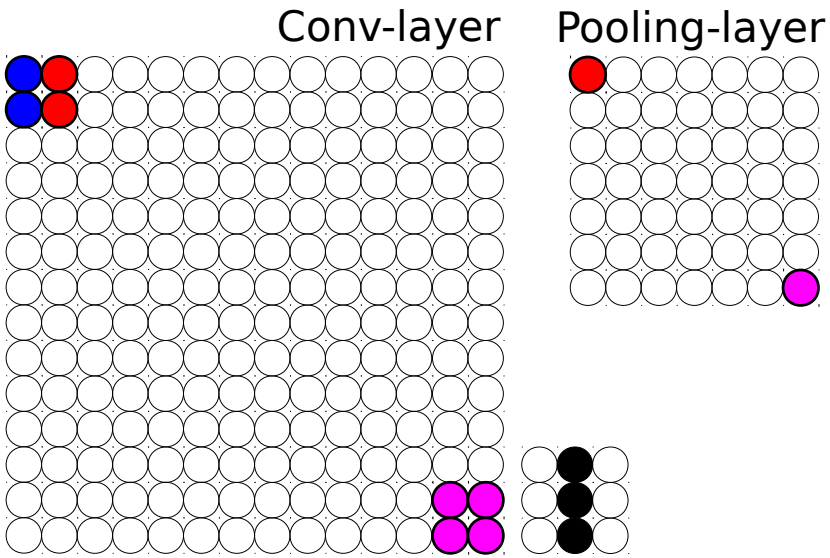
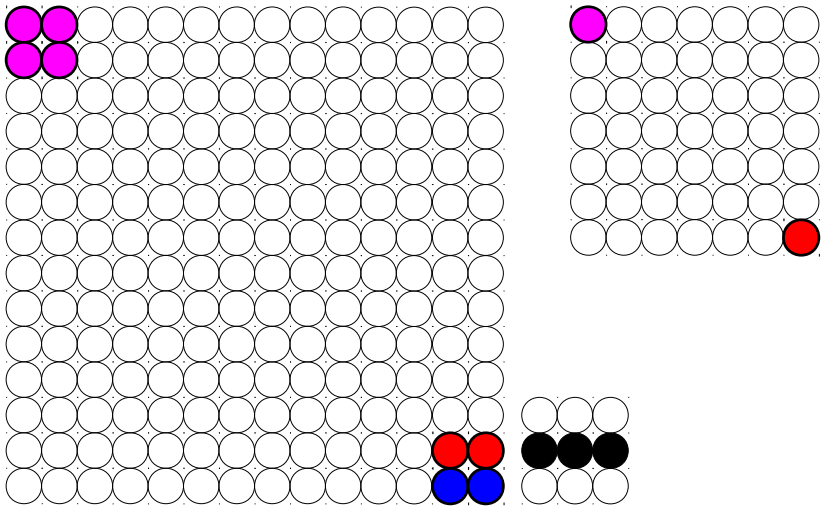
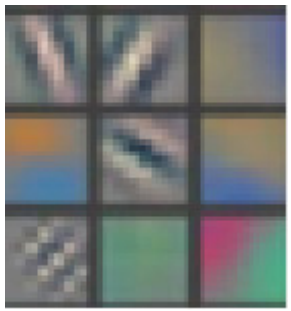




Example of Higher Level Filters



Layer 1

- Top nine activations in feature maps
- Projected to pixel space using a deconvolutional network
- Reconstructed patterns that cause high activations
- Note: Images taken from [Zeiler and Fergus, 2013].

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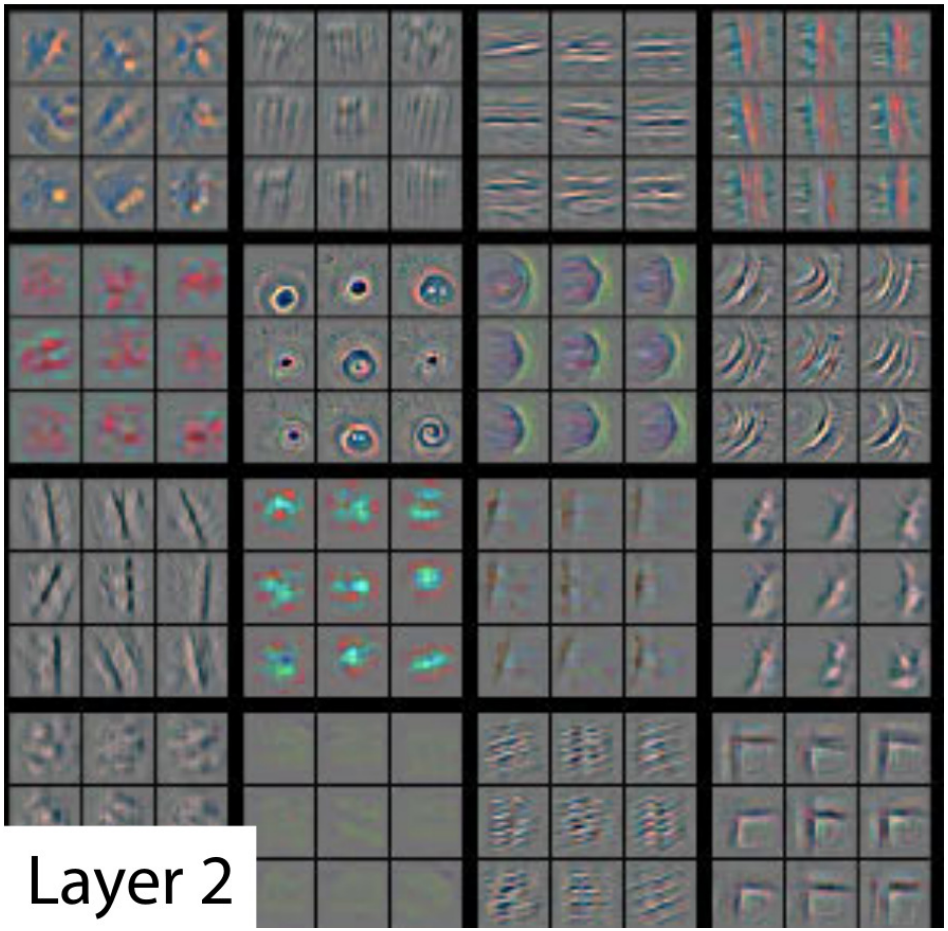

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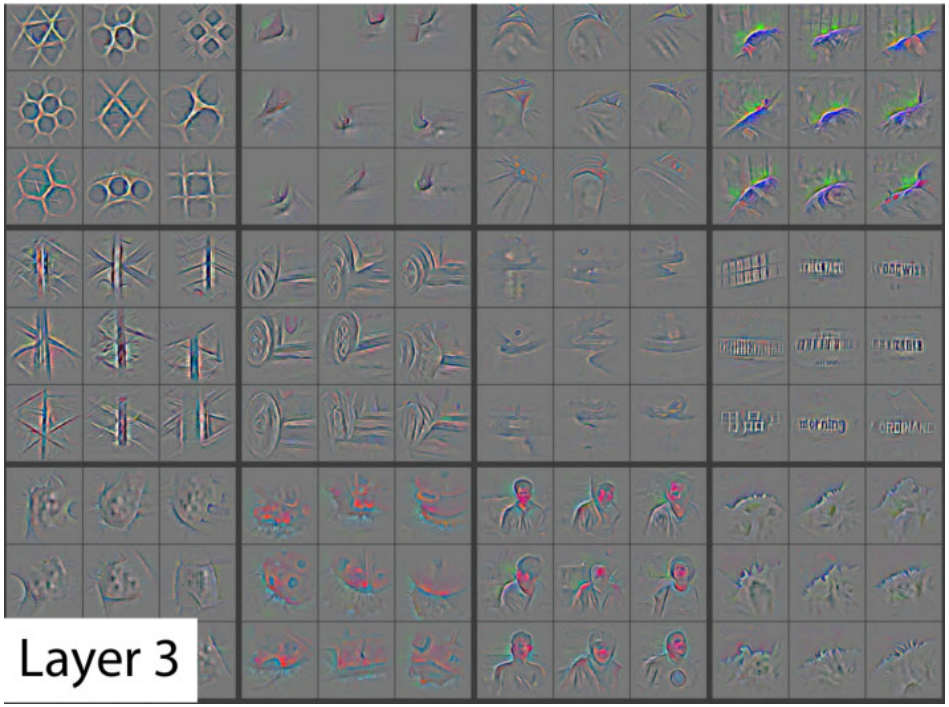

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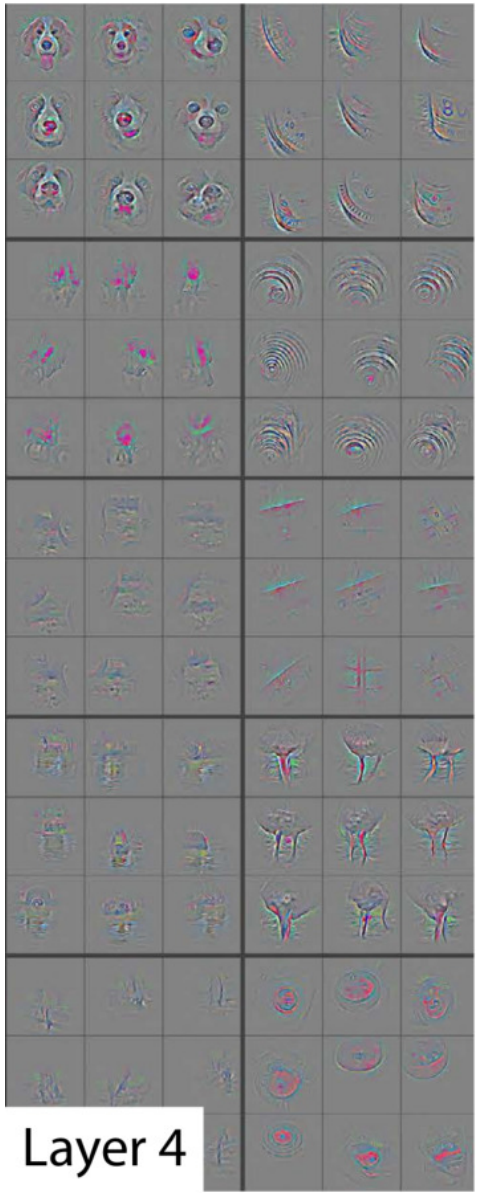

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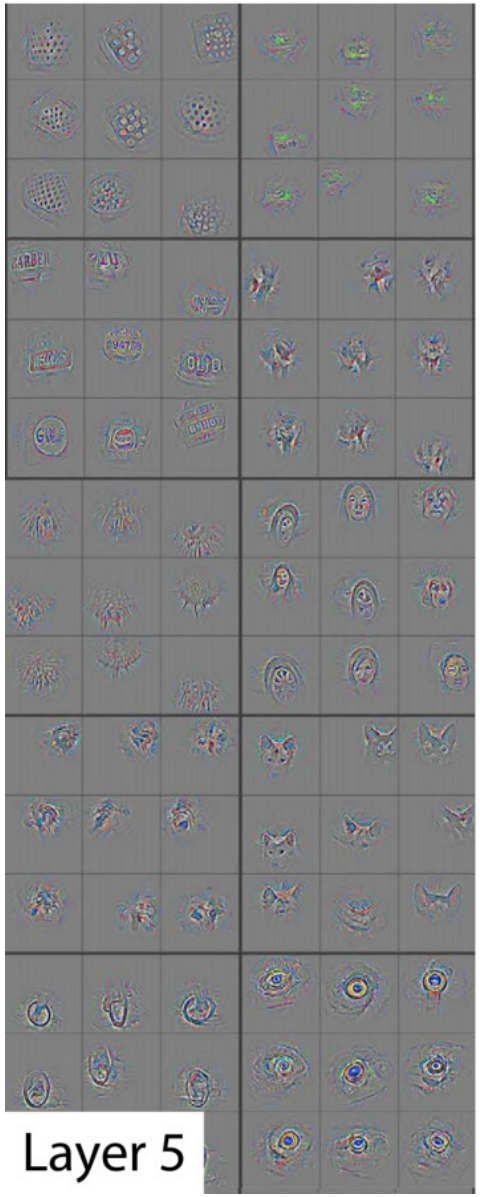

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Architectures

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- Digital digit / character recognition

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- Started the hype
- Similar to LeNet, but deeper and bigger
- Stacked conv-layers
- Image classification (ImageNet Large-Scale Visual Recognition Challenge)
- Trained on 15 million annotated images from over 22,000 categories
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ZF Net (2013)

- Similar to AlexNet
- Trained on 1.3 million annotated images
- Trained on a GTX 580 GPU for twelve days

Architectures

VGG Net (2014)

- Simple and deep: Only 3x3 filters and 2x2 pooling
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Microsoft ResNet (2015)

- 152 layers
- Trained on an 8 GPUs for two to three weeks
- 3.6% error on ImageNet LSVRC (AlexNet: 15.4%)

Common Architectures and Tricks

- Designing good architecture somewhat tricky
- Some designs, or parts of designs, exist that work well
- Usually a good idea to look at papers of common architectures
  - Most of the time, at least some intuition or motivation for choice of layers

Network in a Network

- Alternate between actual conv layers, and conv layers of size $1x1$
- Use the (per pixel) FC layers to compress (reduce channels)
  - Next (actual) convolution faster
  - Deeper network, but less parameters

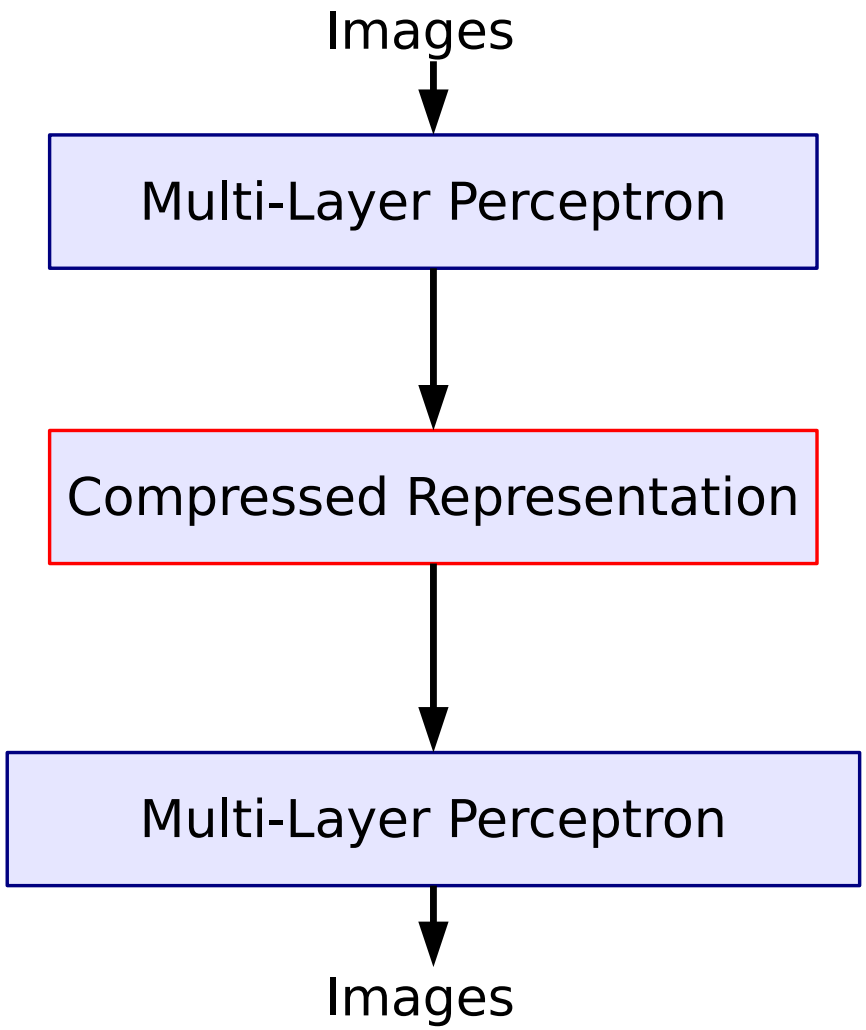
ResNets and Shortcuts

- For deep network, good gradient propagation super important
- ResNet:
  - Concatenation of blocks
  - Each block performs usual operations (conv, relu) ...
  - Result gets added to block's input
  - Neutral/Zero case: Signal passes through unaltered
- Shortcuts:
  - Idea quite similar to ResNets
  - Signal can bypass some layers
  - Signal/Gradient can jump and progress better in deep networks

Inception Module

- Used by Google
- Multiple versions
- Compilation of multiple ideas
- Network in a Network
- Use of small filters (only $3x3$)
- Using two $3x3$ filters same receptive field size as one $5x5$ filter
  - But less parameters

(Convolutional) Auto Encoder



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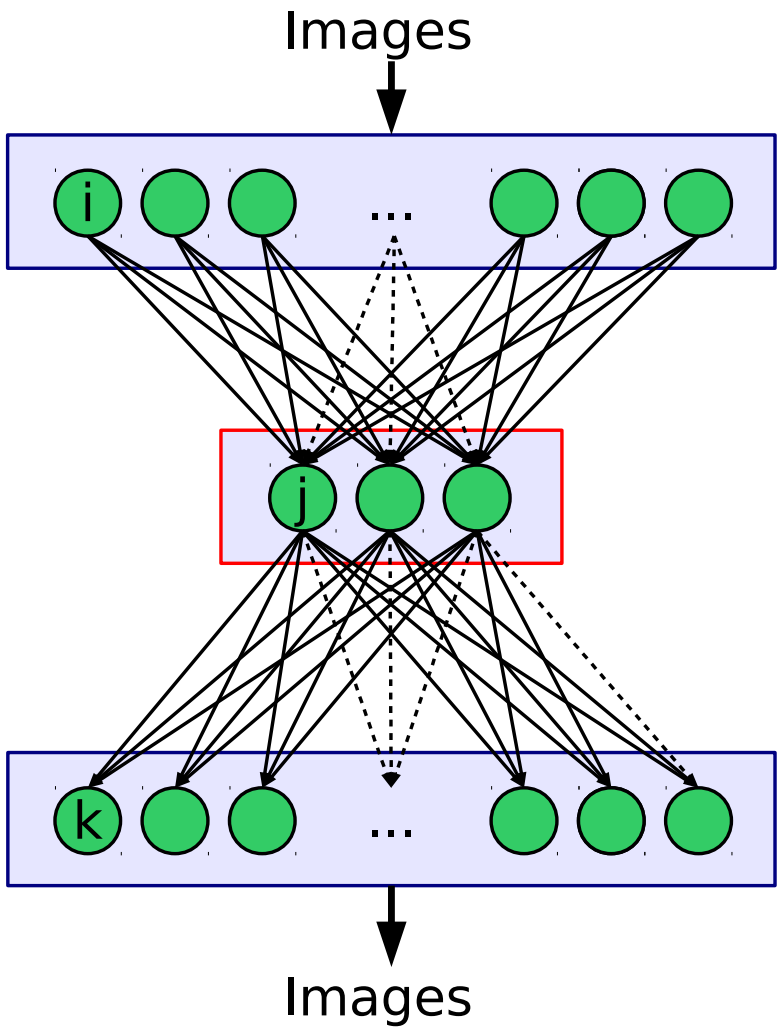
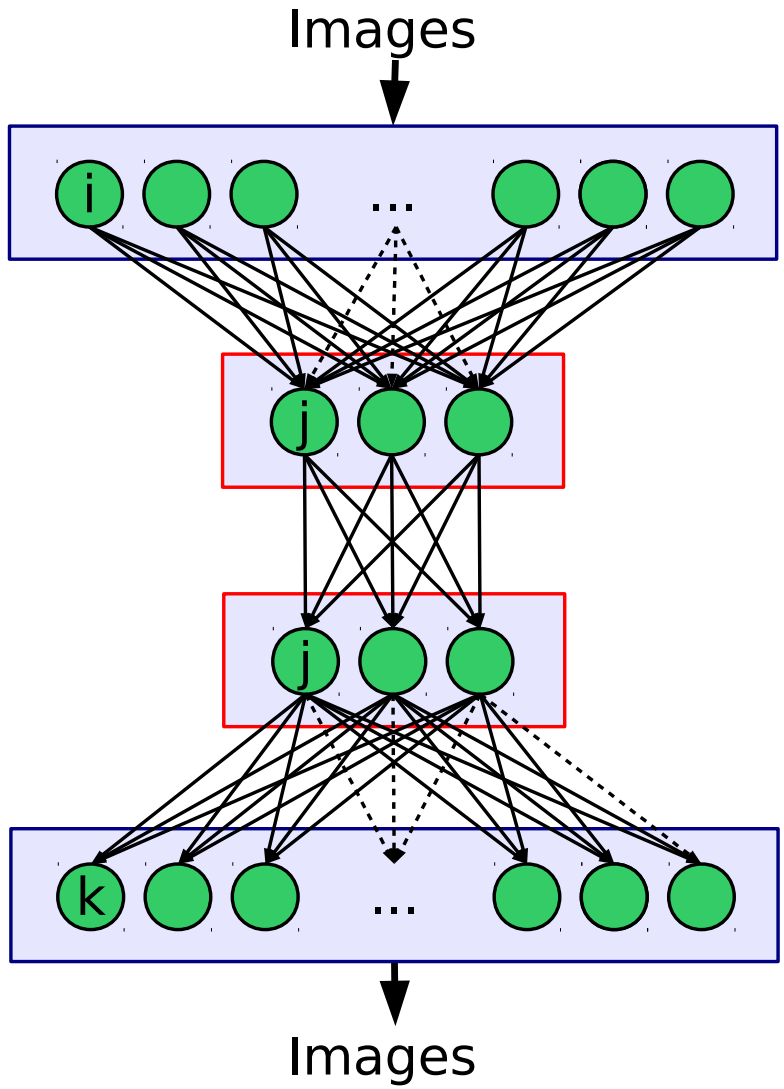


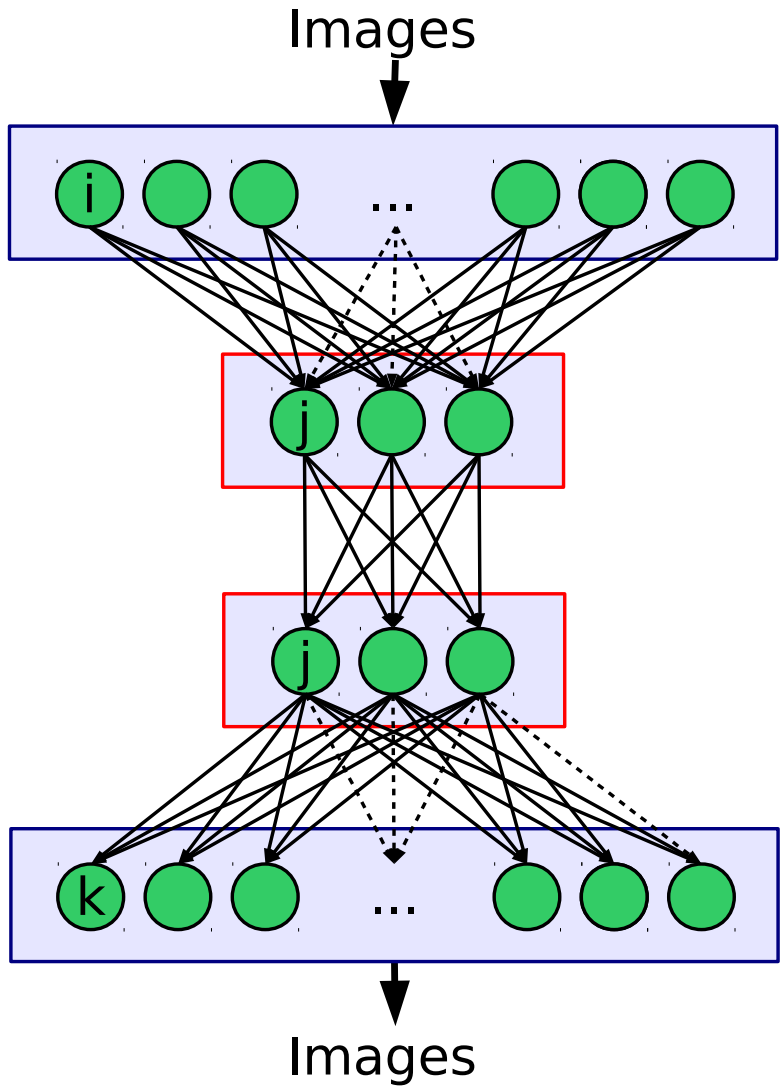
(Convolutional) Auto Encoder

- Stacked Autoencoder



(Convolutional) Auto Encoder

- Stacked Autoencoder
- Problem: Vanishing gradients



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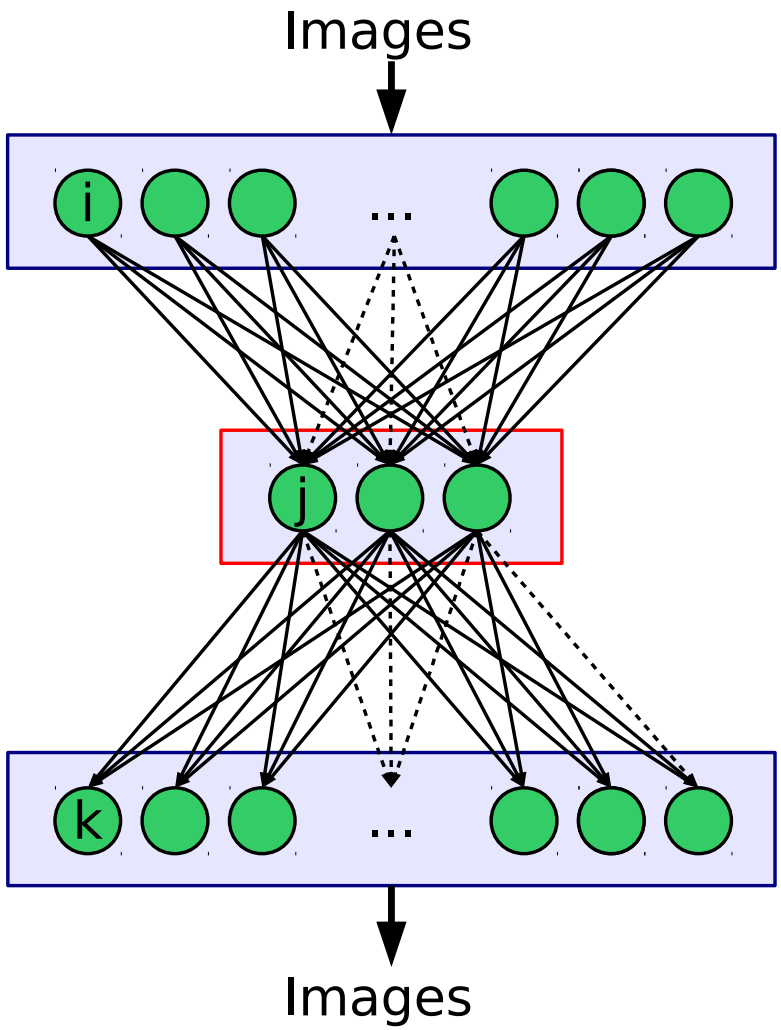
- Solution: Pre-training



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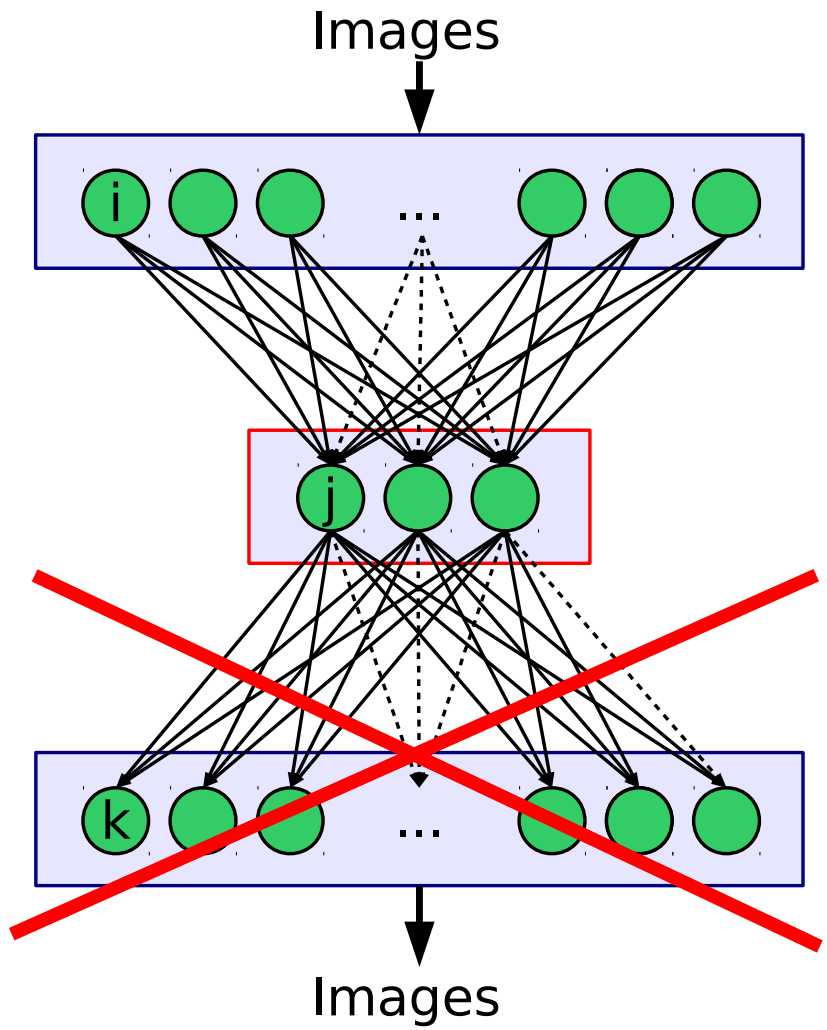

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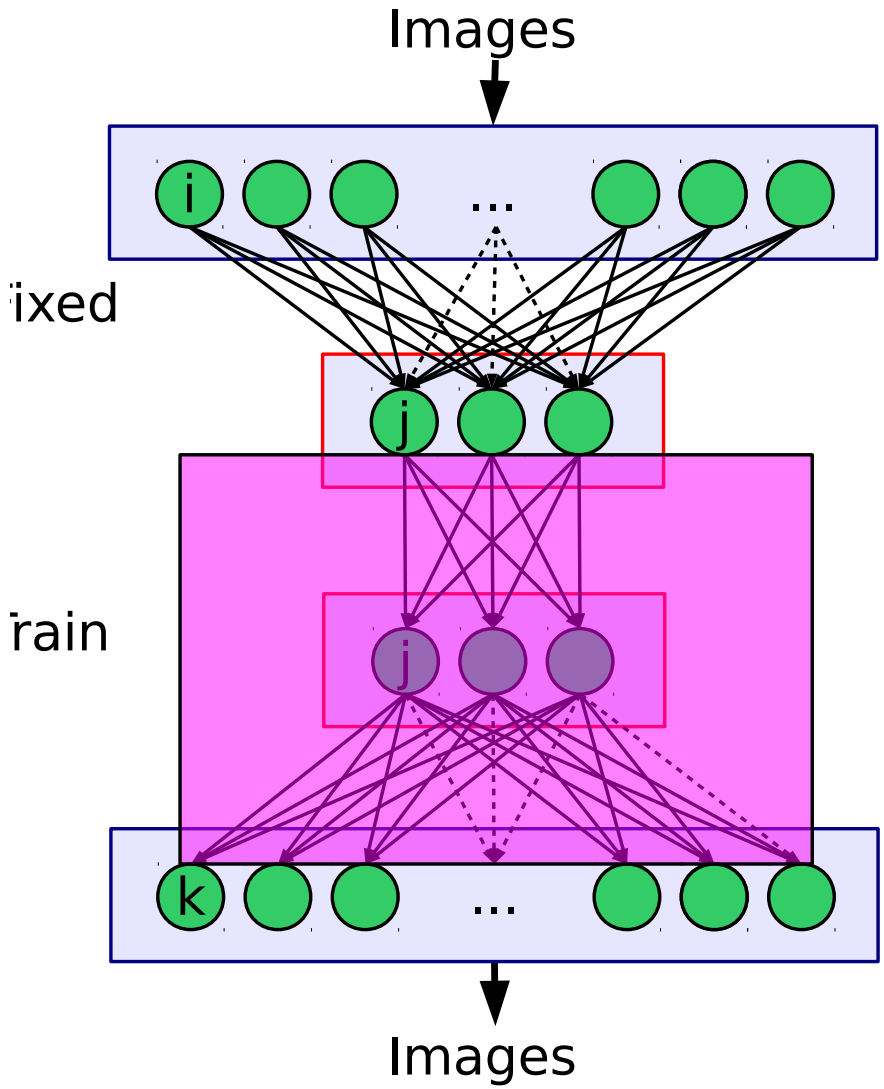

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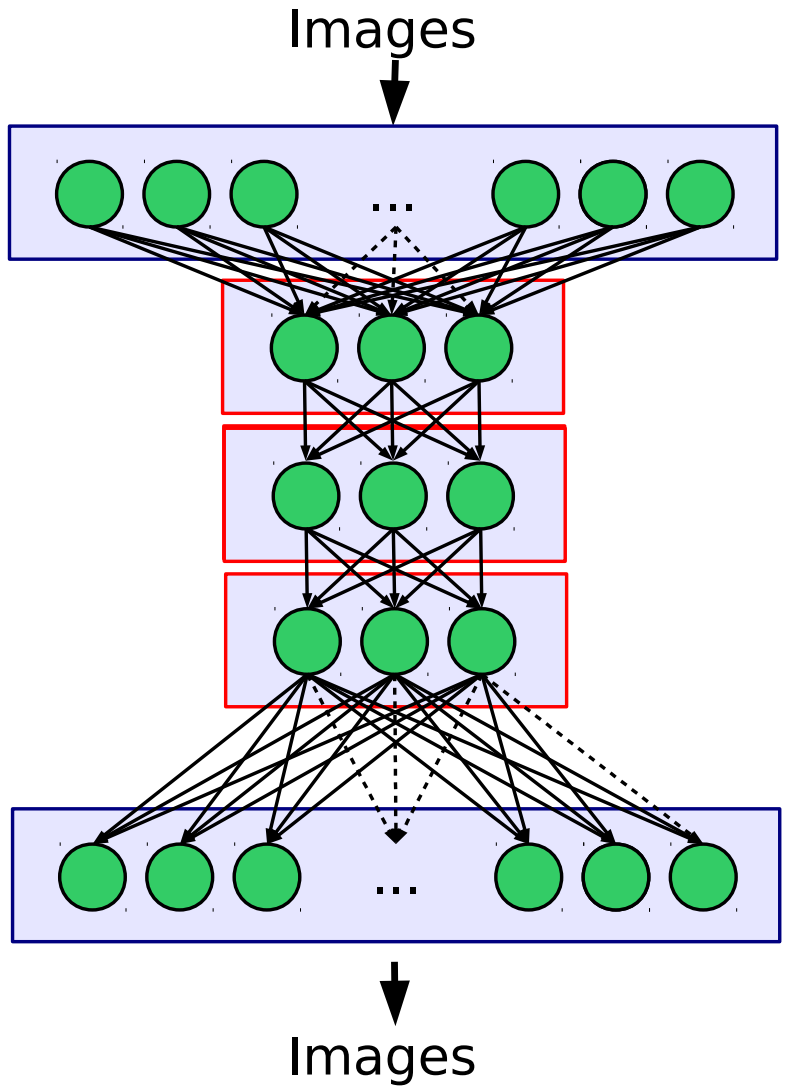

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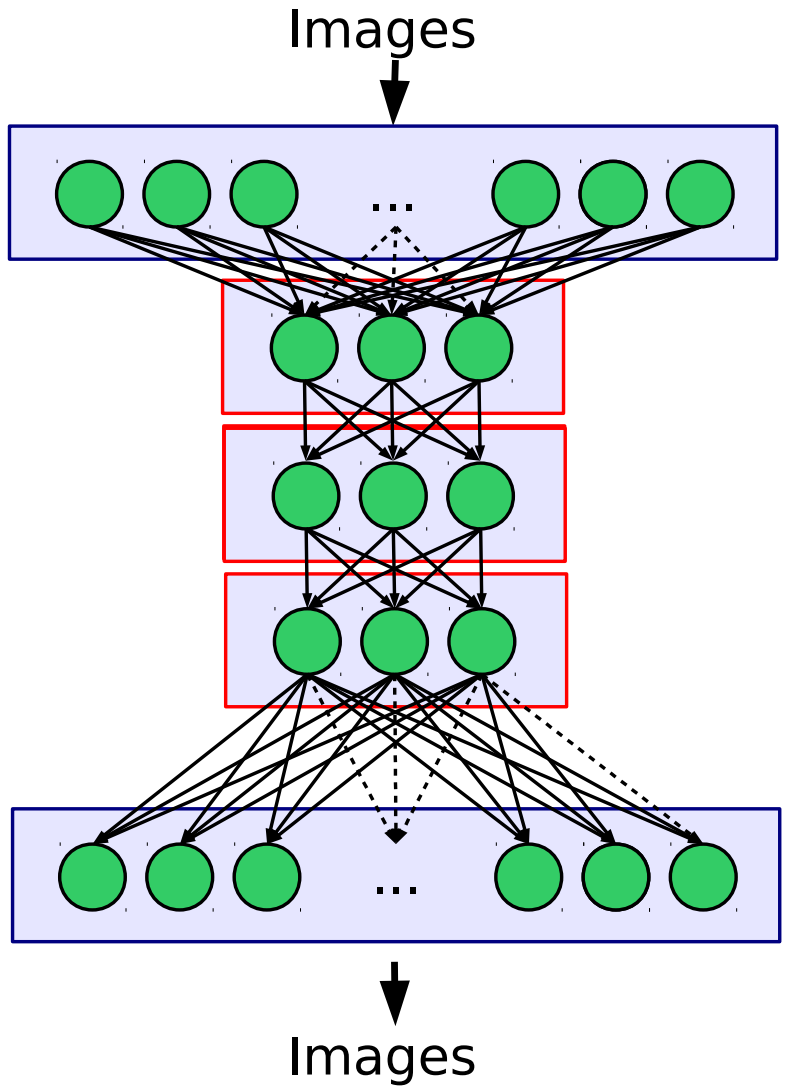
- Application: Deep Learning



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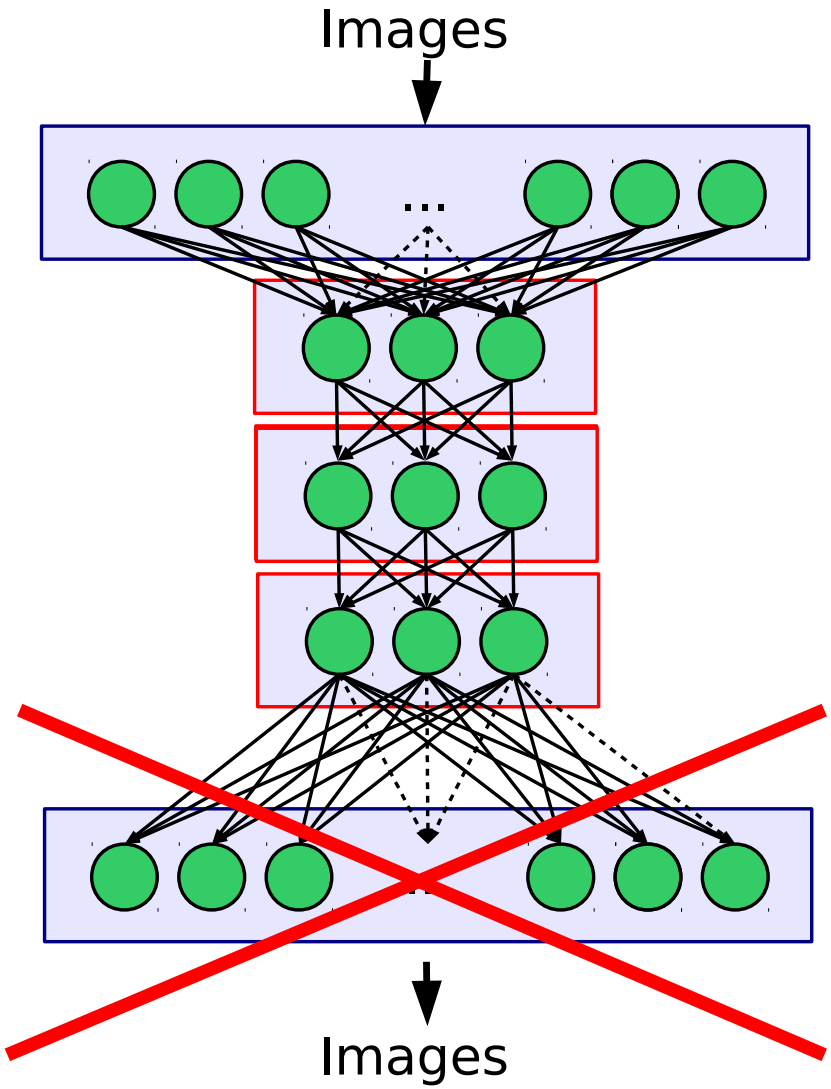
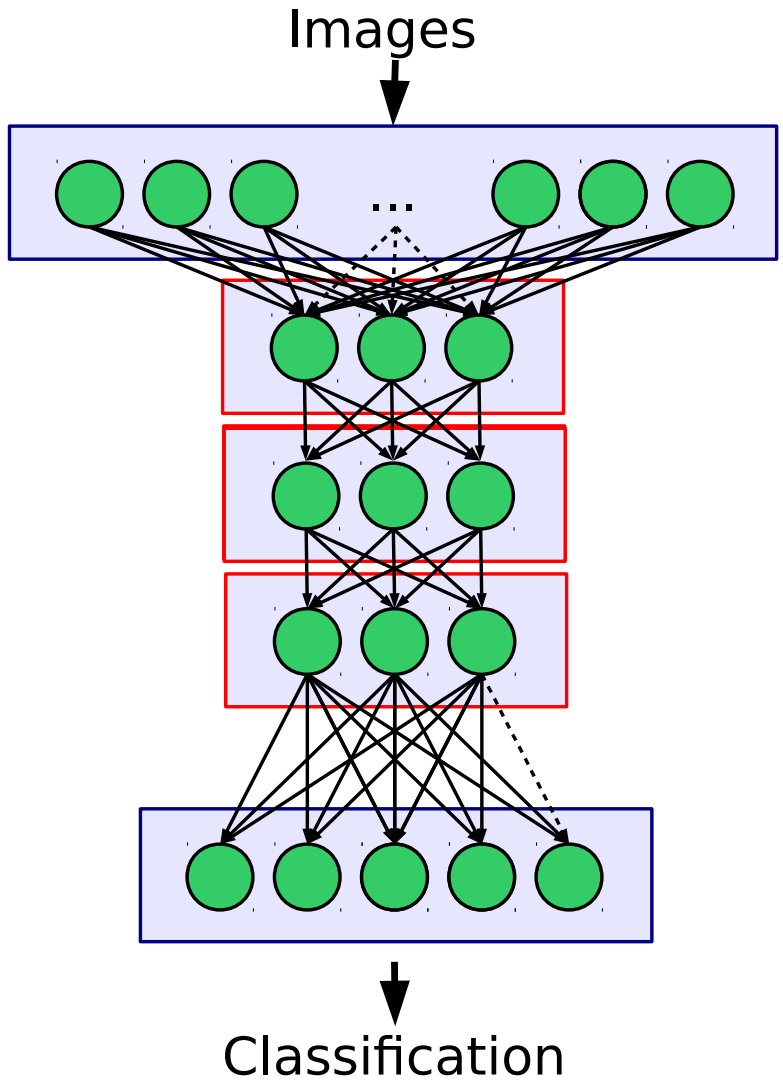
- Solution: Pre-training
- Application: Deep Learning



(Convolutional) Auto Encoder

- Stacked Autoencoder
- Problem: Vanishing gradients
- Solution: Pre-training
  $\rightarrow$ Learn "reasonable" features from unlabeled data
- Application: Deep Learning
  $\rightarrow$ Supervised learning (via Backpropagation) only as refinement



Frameworks

- Implementing fast, multi-channel convolutions just as hard as implementing fast matrix multiplications
- *Use existing tools!*
  - Caffe
  - Tensorflow
  - Torch
- For larger datasets you want to use a (good) GPU!

Caffe

Caffe

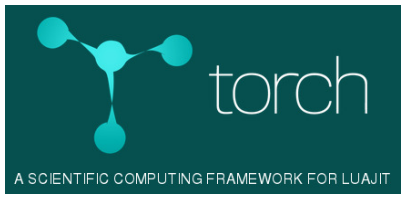
Deep learning framework by BAIR

- Started by Yangqing Jia at UC Berkeley
- Maintained by Berkeley AI Research and many contributers
- Backend in C++, frontends for Python and Matlab
- `http://caffe.berkeleyvision.org/`
- `https://github.com/BVLC/caffe`
- Version 2 now available

Tensorflow

- Developed by Google Brain team
- Python frontend
- `https://www.tensorflow.org/`
- `https://github.com/tensorflow`

Torch



- Lua frontend
- `http://torch.ch/`
- `https://github.com/torch/torch7`

DL Example

Exercise: DL

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R. Hänsch, O. H. (2015a). Feature-independent classification of hyperspectral images by projection-based random forests. In *WHISPERS 2015*.

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Zeiler, M. D. and Fergus, R. (2013). Visualizing and understanding convolutional networks. *CoRR*, abs/1311.2901.

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