Graphical Models

introduction to learning

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Winter 2018

Learning objectives

different goals of learning a graphical model
effect of goals on the learning setup

Where does a graphical model come from?

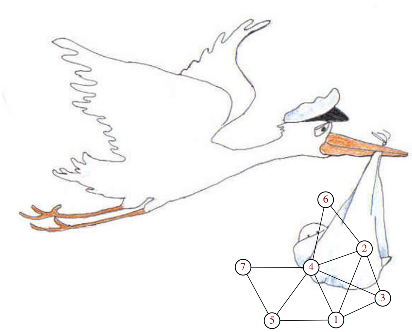

image: http://blog.londolozi.com/

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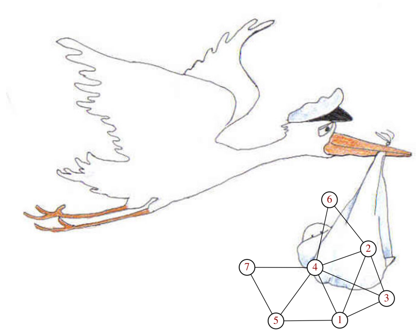
- designed by **domain experts**:
  - more suitable for directed models
    - cond. probabilities are more intuitive than unnormalized factors
    - no need to estimate the partition function



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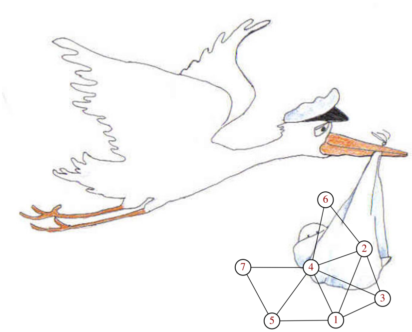

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- **learning** from data:
  - fixed structure:
    - easy for directed models
  - unknown structure
  - fully or partially observed data, hidden variables

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Goals of learning: density estimation

- **assumption**: data is IID sample from a P^*

$$\mathcal{D} = \{X^{(1)}, \ldots, X^{(M)}\} \quad X^{(m)} \sim P^*$$

empirical distribution: $P_{\mathcal{D}}(x) = \frac{1}{|\mathcal{D}|}\mathbb{I}(x \in \mathcal{D})$

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how to compare two log-likelihood values?

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log-likelihood

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Goals of learning: prediction

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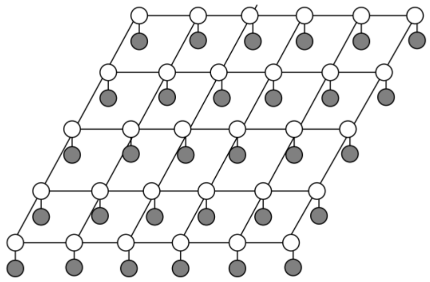

e.g. in image segmentation

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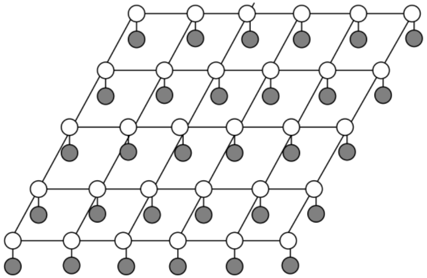

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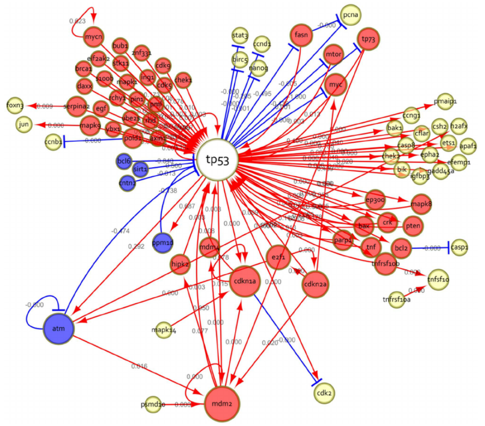
- error measures:
  - 0/1 loss (unforgiving): $\mathbb{E}_{(X,Y)\sim P^*} \mathbb{I}(X = \hat{X}(Y))$
  - Hamming loss: $\mathbb{E}_{(X,Y)\sim P^*} \sum_i \mathbb{I}(X_i = \hat{X}(Y)_i)$
  - conditional log-likelihood: $\mathbb{E}_{(X,Y)\sim P^*} \log \hat{P}(X \mid Y)$
    - takes prediction uncertainty into account

Goals of learning: knowledge discovery

given $\mathcal{D} = \{(X^{(m)})\}$

interested in learning $\mathcal{G}$ or $\mathcal{H}$

finding conditional independencies or causal relationships



E.g. in gene regulatory network

image credit: Chen et al., 2014

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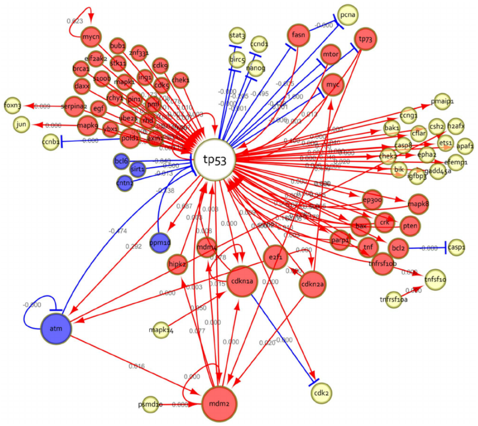
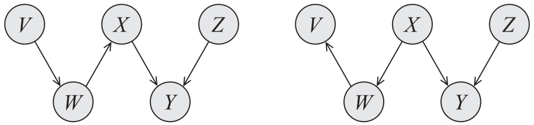


E.g. in gene regulatory network

not always uniquely **identifiable**

Recall two DAGs are I-equivalent if $\mathcal{I}(\mathcal{G}) = \mathcal{I}(\mathcal{G}')$



- same undirected skeleton
- same immoralities

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bias-variance trade-off

learning *ideally* minimizes some risk (expected loss) $\mathbb{E}_{X \sim P^*}[loss(X)]$

in reality we use empirical risk $\mathbb{E}_{x \in \mathcal{D}}[loss(x)]$

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if our model is expressive we can overfit

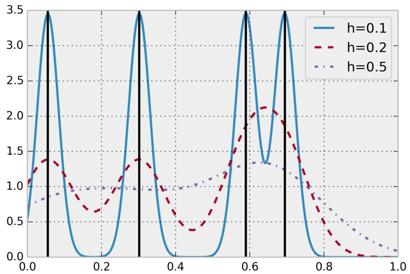
high variance

low *empirical* risk does not translate to low risk

our model does not generalize to samples outside $\mathcal{D}$

as measured by a validation set

different choices of $\mathcal{D} \sim P^*$ produce very different models $\hat{P}$



overfitting in density estimation

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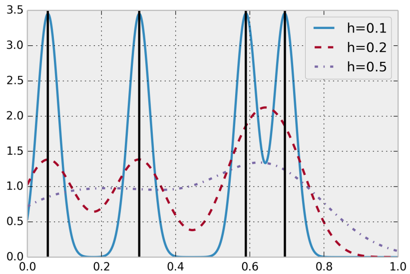

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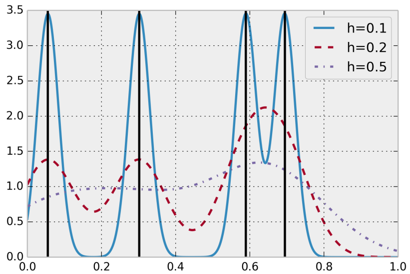

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a solution: penalize model complexity **regularization**

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Discreminative vs generative training

if the goal is prediction: $\hat{P}(X \mid Y)$

- **Generative:** learn $\hat{P}(X, Y)$ and condition on Y (e.g., MRF)
- **Discriminative:** directly learn $\hat{P}(X \mid Y)$ (e.g., CRF)

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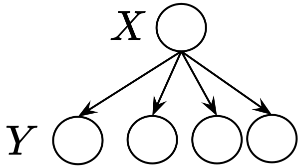
Example naive Bayes vs logistic regression



- trained generatively (log-likelihood)
- works better on small datasets (higher bias)
- unnecessary cond. ind. assumptions about Y
- can deal with missing values & learn from unlabeled data

Naive Bayes $P(X \mid Y) \propto P(X)P(Y \mid X)$

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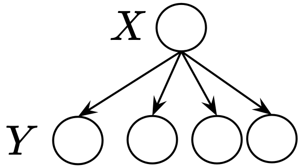

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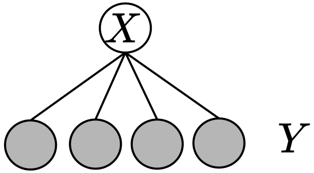


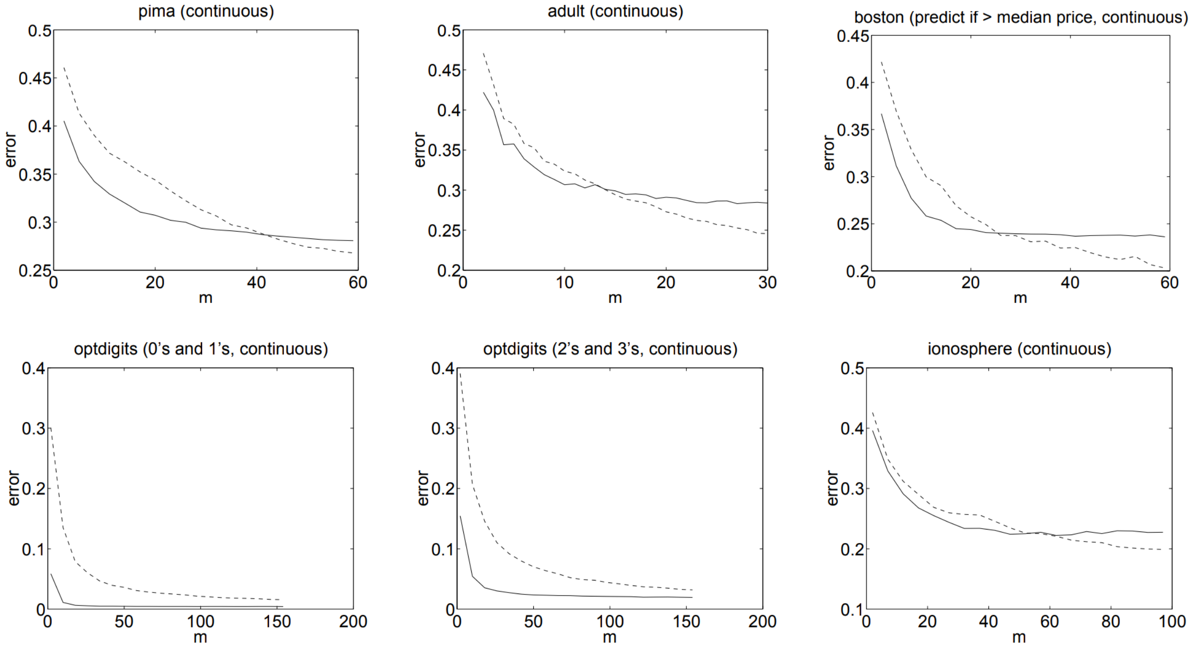
logistic regression $P(X = 1|Y) = \sigma(WY + b)$

Discreminative vs generative training

Example naive Bayes vs logistic regression on UCI dataset

naive Bayes

logistic regression



from: Ng & Jordan 2001

summary

- learning can have different objectives:
  - density estimation
    - calculating P(x)
    - sampling from P (generative modeling)
  - prediction (conditional density estimation)
    - discriminative and generative modeling
  - knowledge discovery
- expressed as empirical risk minimization
  - bias-variance trade-off
  - regularize the model