

## Lecture 8: When Models Meet Data

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Mathematics for Machine Learning

<https://yung-web.github.io/home/courses/mathml.html>

KAIST EE

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- (1) Data, Models, and Learning
- (2) Models as Functions: Empirical Risk Minimization
- (3) Models as Probabilistic Models: Parameter Estimation (ML and MAP)
- (4) Probabilistic Modeling and Inference
- (5) Directed Graphical Models
- (6) Model Selection

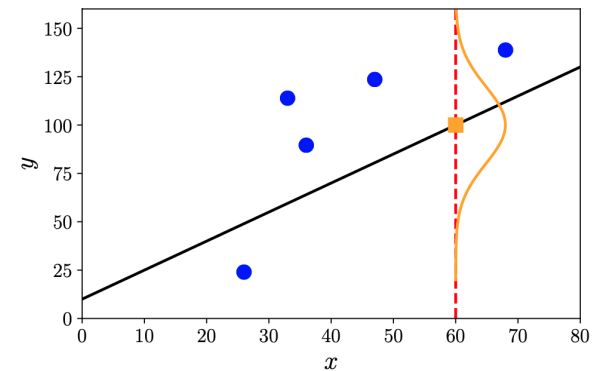
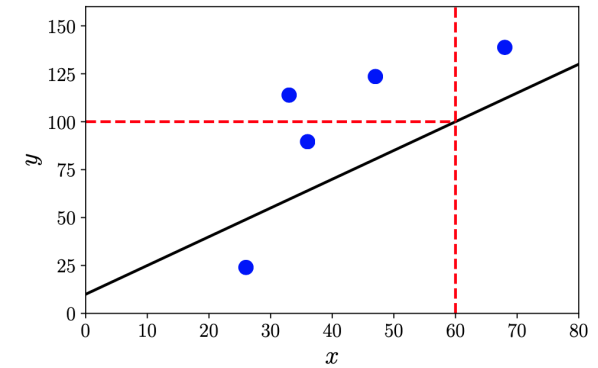
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- Three major components of a machine learning system
  1. Data:  $\{(\mathbf{x}_1, y_1), \dots, (\mathbf{x}_n, y_n), \dots, (\mathbf{x}_N, y_N)\}$
  2. Models: deterministic functions or probabilistic models
  3. Learning: Training, and prediction/inference
- Good machine learning models: Perform well for unseen (untrained) data
- Machine learning algorithm: training and prediction

- Tabular format or not, numerical or not, good feature extraction etc.
- Assume that data is given as  $D$ -dimensional vector  $\mathbf{x}_n$  of real numbers, each called **features**, **attributes**, or **covariates**.
- Dataset: consisting of data points or examples  $\{\mathbf{x}_1, \mathbf{x}_2, \dots, \mathbf{x}_N\}$
- In supervised learning,  $\{(\mathbf{x}_1, y_1), \dots, (\mathbf{x}_n, y_n), \dots, (\mathbf{x}_N, y_N)\}$ , where  $y_n$  is the **label** (or target, response variable, or annotation).
- Better representation of data as vectors
  - finding lower-dimensional approximations of the original feature vector (e.g., PCA via SVD or EVD)
  - using nonlinear higher-dimensional combinations of the original feature vector (e.g., feature map and kernel)

# Models: Functions vs. Probabilistic Models

- Now, the business of constructing a predictor
- Models as **functions**
  - $f : \mathbb{R}^D \mapsto \mathbb{R}$ .
  - **Example.**  $f(\mathbf{x}) = \boldsymbol{\theta}^T \mathbf{x} + \theta_0$ , Unknown parameter:  $\boldsymbol{\theta}, \theta_0$
- Models as **probabilistic models**
  - model our uncertainty due to the **observation process** and our uncertainty in the **parameters of our model**
  - predictors should be able to express some sort of uncertainty via probabilistic models
  - Parameters: parameters of a chosen probabilistic model (e.g., mean and variance of Gaussian)



Three algorithmic phases

- (1) Prediction or inference: via function or probabilistic models
- (2) Training or parameters estimation
  - fixed parameter assumption (non-probabilistic) or Bayesian approach (probabilistic)
  - non-probabilistic: e.g., empirical risk minimization
  - probabilistic: e.g., ML (Maximum Likelihood), MAP (Maximum A Posteriori)
  - cross-validation: simulation of performing for unseen data
  - regularization/prior: balancing models between training and unseen data
- (3) Hyperparameter tuning or model selection

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- Predictor as a function
- Given  $\{(\mathbf{x}_1, y_1), \dots, (\mathbf{x}_n, y_n), \dots, (\mathbf{x}_N, y_N)\}$ , estimate a predictor  $f(\cdot, \boldsymbol{\theta}) : \mathbb{R}^D \mapsto \mathbb{R}$
- Find a good parameter  $\boldsymbol{\theta}^*$ , such that  $f(\mathbf{x}_n, \boldsymbol{\theta}^*) = \hat{y}_n \approx y_n$ , for all  $n = 1, \dots, N$
- **Example.** Affine function: By adding the unit feature  $x^{(0)} = 1$  and  $\theta_0$ , i.e.,  
 $\mathbf{x}_n = [1, x_n^{(1)}, \dots, x_n^{(D)}]^\top$ ,  $\boldsymbol{\theta} = [\theta_0, \theta_1, \dots, \theta_D]^\top$   
$$f(\mathbf{x}_n, \boldsymbol{\theta}) = \boldsymbol{\theta}^\top \mathbf{x}_n = \theta_0 + \sum_{d=1}^D \theta_d x_n^{(d)}$$
- **Example.** Neural network: Complex non-linear function

- Training set:  $\{(\mathbf{x}_1, y_1), \dots, (\mathbf{x}_n, y_n), \dots, (\mathbf{x}_N, y_N)\}$ , an example matrix<sup>1</sup>  
 $\mathbf{X} := [\mathbf{x}_1, \dots, \mathbf{x}_N]^T \in \mathbb{R}^{N \times D}$ , a label vector  $\mathbf{y} := [y_1, \dots, y_N]^T$ ,
- Average loss, empirical risk

$$R_{\text{emp}}(f, \mathbf{X}, \mathbf{y}) = \frac{1}{N} \sum_{n=1}^N \ell(y_n, \hat{y}_n)$$

- Goal: Minimizing empirical risk
- **Example.** The squared loss function  $\ell(y_n, \hat{y}_n) = (y_n - \hat{y}_n)^2$  leads to:

$$\min_{\boldsymbol{\theta} \in \mathbb{R}^D} \frac{1}{N} \|\mathbf{y} - \mathbf{X}\boldsymbol{\theta}\|^2$$

- **Question.** Ultimate goal: Minimizing expected risk (for unseen data)  
 $R_{\text{true}} = \mathbb{E}_{\mathbf{x}, y}[\ell(y, f(\mathbf{x}))]$ ?

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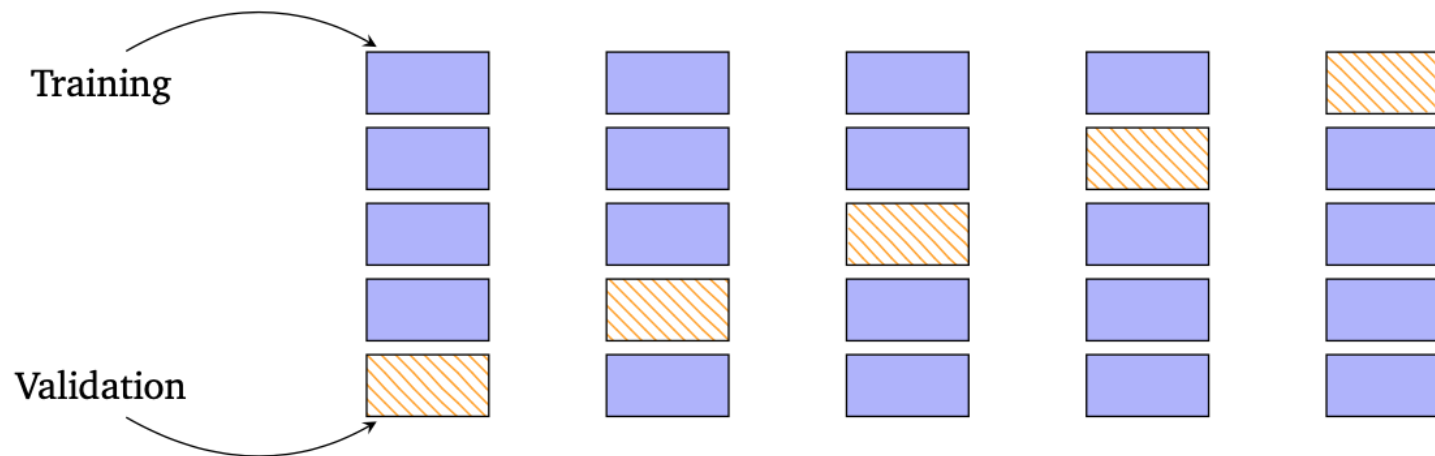
<sup>1</sup>In other chapters, we often use  $D \times N$  example matrix by defining it as  $\mathbf{X} := [\mathbf{x}_1, \dots, \mathbf{x}_N]$ . **L10(4)**

- The predictor fits too closely to the training data and does not generalize well to new data
- Need to somehow bias the search for the minimizer of empirical risk by introducing a **penalty term**
- **Regularization**: compromise between accurate solution of empirical risk minimization and the size or complexity of the solution.
- **Example**. Regularized Least Squares

$$\min_{\boldsymbol{\theta} \in \mathbb{R}^D} \frac{1}{N} \|\mathbf{y} - \mathbf{X}\boldsymbol{\theta}\|^2 + \lambda \|\boldsymbol{\theta}\|^2$$

- $\|\boldsymbol{\theta}\|^2$ : regularizer,  $\lambda$ : regularization parameter

# Cross-Validation for Generalization Performance



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- Idea: define a function of the parameters called **likelihood function**.
- Negative log-likelihood for data  $\mathbf{x}$  and a family of probability densities  $\mathbb{P}(\mathbf{x} \mid \boldsymbol{\theta})$  parameterized by  $\boldsymbol{\theta}$ :

$$\mathcal{L}_{\mathbf{x}}(\boldsymbol{\theta}) = \mathcal{L}(\boldsymbol{\theta}) := -\log \mathbb{P}(\mathbf{x} \mid \boldsymbol{\theta})$$

- $\mathcal{L}(\boldsymbol{\theta})$ : how likely a particular setting of  $\boldsymbol{\theta}$  is for the observations  $\mathbf{x}$ .
- **MLE**: Find  $\boldsymbol{\theta}$  such that  $\mathcal{L}(\boldsymbol{\theta})$  is **minimized** (i.e., likelihood is **maximized**)

- The set of iid examples  $(\mathbf{x}_1, y_1), \dots, (\mathbf{x}_N, y_N)$
- $\mathcal{X} = \{\mathbf{x}_1, \dots, \mathbf{x}_N\}$  and  $\mathcal{Y} = \{y_1, \dots, y_N\}$
- Negative log-likelihood

$$\mathcal{L}(\boldsymbol{\theta}) = -\log \mathbb{P}(\mathcal{Y} \mid \mathcal{X}, \boldsymbol{\theta}) = \sum_{n=1}^N \log \mathbb{P}(y_n \mid \mathbf{x}_n, \boldsymbol{\theta})$$

- **Example.** Assume independent Gaussian noise  $\mathcal{N}(0, \sigma^2)$  and linear model  $y_n = \mathbf{x}_n^\top \boldsymbol{\theta}$  for prediction. Then,  $Y_n \mid (\mathbf{x}_n, \boldsymbol{\theta}) \sim \mathcal{N}(\mathbf{x}_n^\top \boldsymbol{\theta}, \sigma^2)$ .

$$\mathcal{L}(\boldsymbol{\theta}) = -\sum_{n=1}^N \log \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(-\frac{(y_n - \mathbf{x}_n^\top \boldsymbol{\theta})^2}{2\sigma^2}\right) = \frac{1}{2\sigma^2} \sum_{n=1}^N (y_n - \mathbf{x}_n^\top \boldsymbol{\theta})^2 - \sum_{n=1}^N \log \frac{1}{\sqrt{2\pi\sigma^2}}$$

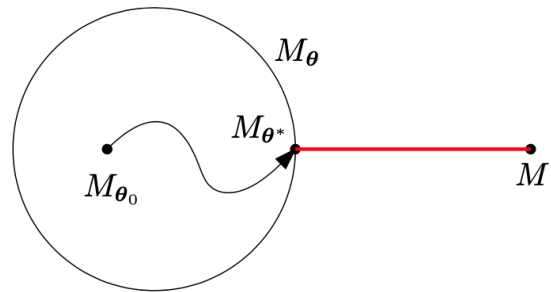
- What if we have some **prior knowledge** about  $\theta$ ? Then, how should we change our knowledge about  $\theta$  after observing data  $\mathbf{x}$ ?
- Compute a posteriori distribution (using Bayes' Theorem) and find  $\theta$  that maximizes the distribution:

$$\max_{\theta} \mathbb{P}(\theta | \mathbf{x}) = \max_{\theta} \frac{\mathbb{P}(\mathbf{x} | \theta) \mathbb{P}(\theta)}{\mathbb{P}(\mathbf{x})} \iff \min_{\theta} \left( -\log \mathbb{P}(\theta | \mathbf{x}) \right)$$

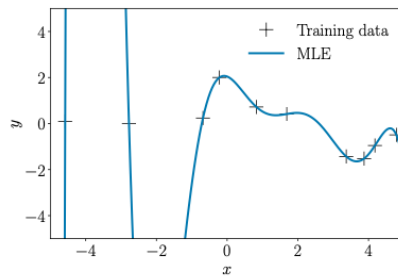
- In finding the optimal  $\theta$ ,  $\mathbb{P}(\mathbf{x})$  can be ignored
- ML and MAP: Bridging the non-probabilistic and probabilistic worlds as it explicitly acknowledges the need for a prior distribution, yet producing a **point estimate** (one single parameter return).



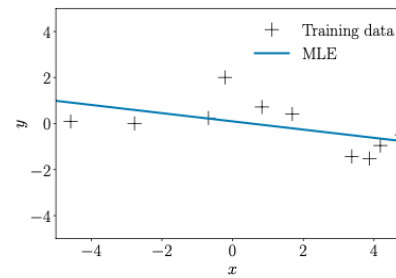
- Model class  $M_\theta$  vs. Right model  $M^*$



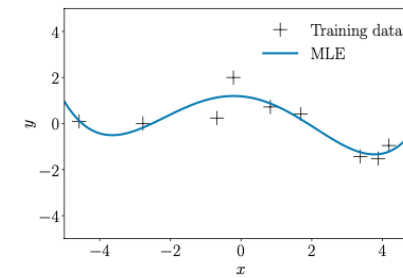
- Overfitting vs. Underfitting vs. Good fitting



(a) Overfitting



(b) Underfitting.



(c) Fitting well.

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- Many machine learning tasks: prediction of future events and decision making
- Often build (probabilistic) models that describe the **generative process** that generates the observed data
- In probabilistic modeling, the joint distribution  $\mathbb{P}(\mathbf{x}, \boldsymbol{\theta})$  of the observed variables  $\mathbf{x}$  and the hidden parameters  $\boldsymbol{\theta}$  encapsulate the key information
  - Given: **prior**  $\mathbb{P}(\boldsymbol{\theta})$  and **likelihood**  $\mathbb{P}(\mathbf{x}|\boldsymbol{\theta})$
  - **Joint dist.** from prior and likelihood:  $\mathbb{P}(\mathbf{x}, \boldsymbol{\theta}) = \mathbb{P}(\mathbf{x}|\boldsymbol{\theta})\mathbb{P}(\boldsymbol{\theta})$
  - We get: **marginal likelihood**  $\mathbb{P}(\mathbf{x}) = \int \mathbb{P}(\mathbf{x}, \boldsymbol{\theta})d\boldsymbol{\theta}$  and **posterior**  $\mathbb{P}(\boldsymbol{\theta}|\mathbf{x}) = \frac{\mathbb{P}(\mathbf{x}, \boldsymbol{\theta})}{\mathbb{P}(\mathbf{x})}$

# Fully Bayesian vs. ML/MAP

Given the data set  $\mathcal{X}$ , we want to predict  $A$ , i.e.,  $\mathbb{P}(A | \mathcal{X})$

- **ML**: Easy (high), Exact (low)

$$\mathbb{P}(A | \mathcal{X}) \approx \mathbb{P}(A | \theta), \quad \theta = \arg \max \mathbb{P}(\mathcal{X} | \theta)$$

- **MAP**: Easy (mid), Exact (mid)

$$\mathbb{P}(A | \mathcal{X}) \approx \mathbb{P}(A | \theta), \quad \theta = \arg \max \mathbb{P}(\theta | \mathcal{X})$$

- **Fully Bayesian**: Easy (low), Exact (high)

- predictive inference, use of posterior predictive distribution, bayesian prediction
- remove dependence on the model parameters  $\theta$

$$\mathbb{P}(A | \mathcal{X}) = \int \mathbb{P}(A | \theta) \mathbb{P}(\theta | \mathcal{X}) d\theta$$

- Only possible by getting the full posterior distribution  $\mathbb{P}(\theta | \mathcal{X})$

- For a data set  $\mathcal{X}$ , a parameter prior  $\mathbb{P}(\boldsymbol{\theta})$ , and a likelihood function, the posterior is:

$$\mathbb{P}(\boldsymbol{\theta} \mid \mathcal{X}) = \frac{\mathbb{P}(\mathcal{X} \mid \boldsymbol{\theta})\mathbb{P}(\boldsymbol{\theta})}{\mathbb{P}(\mathcal{X})}, \quad \mathbb{P}(\mathcal{X}) = \int \mathbb{P}(\mathcal{X} \mid \boldsymbol{\theta})\mathbb{P}(\boldsymbol{\theta}) \, d\boldsymbol{\theta}$$

- Implementation hardness
  - Bayesian inference requires to solve integration, which is often challenging. In particular, a conjugate prior is not chosen, the integration is not analytically tractable.
  - Approximation techniques: MCMC (Markov Chain Monte Carlo), Laplace approximation, variational inference, expectation propagation

- Including latent variables in the model  $\rightarrow$  contributing to the interpretability of the model
- General discussions here would be applied the following examples later
  - PCA for dimensionality reduction L10(7)
  - Gaussian mixture models for density estimation L11(3)
- In latent-variable models (LVMs)<sup>2</sup>,
  - Given: **prior**  $\mathbb{P}(\mathbf{z})$  and **likelihood**  $\mathbb{P}_{\theta}(\mathbf{x}|\mathbf{z})$
  - **Joint dist.** from prior and likelihood:  $\mathbb{P}_{\theta}(\mathbf{x}, \mathbf{z}) = \mathbb{P}_{\theta}(\mathbf{x}|\mathbf{z})\mathbb{P}(\mathbf{z})$
  - Our interest: **marginal likelihood**  $\mathbb{P}_{\theta}(\mathbf{x})$  and **posterior**  $\mathbb{P}_{\theta}(\mathbf{z}|\mathbf{x})$

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<sup>2</sup>In our note, we express the dependence on the model parameters  $\theta$  using subscript notations, e.g.,  $\mathbb{P}_{\theta}(\mathbf{x}|\mathbf{z})$  rather than  $\mathbb{P}(\mathbf{x}|\mathbf{z}, \theta)$  to highlight the role of  $\mathbf{z}$ .

- Assuming we know  $\theta$ , to generate a data sample from the model (i) sample  $\mathbf{z}$  from  $\mathbb{P}(\mathbf{z})$  and (ii) sample  $\mathbf{x}$  from  $\mathbb{P}_{\theta}(\mathbf{x}|\mathbf{z})$
- **Inference.** computing the **posterior distribution**  $\mathbb{P}_{\theta}(\mathbf{z}|\mathbf{x})$ :

$$\mathbb{P}_{\theta}(\mathbf{z}|\mathbf{x}) = \frac{\mathbb{P}_{\theta}(\mathbf{x}, \mathbf{z})}{\mathbb{P}_{\theta}(\mathbf{x})} = \frac{\mathbb{P}_{\theta}(\mathbf{x}, \mathbf{z})}{\int \mathbb{P}_{\theta}(\mathbf{x}, \mathbf{z}) d\mathbf{z}}$$

- This requires to solve the sub-problem of computing the **marginal likelihood** of the observation:

$$\mathbb{P}_{\theta}(\mathbf{x}) = \int \mathbb{P}_{\theta}(\mathbf{x}, \mathbf{z}) d\mathbf{z}$$

## LVM (3): Why the posterior distribution $\mathbb{P}_{\theta}(\mathbf{z}|\mathbf{x})$ ?

- **Explanation of the observation.** Allows us to figure out which latent configurations could have plausibly generated the observation data samples.
- **Learning of model parameters  $\theta$ .** Training LVMs to estimate  $\theta$  (e.g., ML) requires  $\mathbb{P}_{\theta}(\mathbf{z}|\mathbf{x})$  in its inner loops

marginal likelihood  $\mathbb{P}_{\theta}(\mathbf{x}) \implies$  posterior distribution  $\mathbb{P}_{\theta}(\mathbf{z}|\mathbf{x}) \implies \theta_{\text{ML}}$



- In ML, we need the gradient of the marginal log-likelihood. For a data sample  $\mathbf{x}$ ,

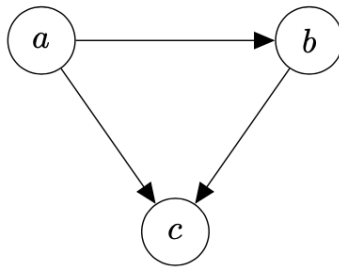
$$\begin{aligned}\nabla_\theta \log p_\theta(\mathbf{x}) &= \frac{\nabla_\theta p_\theta(\mathbf{x})}{p_\theta(\mathbf{x})} = \frac{\int \nabla_\theta p_\theta(\mathbf{x}, \mathbf{z}) d\mathbf{z}}{p_\theta(\mathbf{x})} = \frac{\int p_\theta(\mathbf{x}, \mathbf{z}) \nabla_\theta \log p_\theta(\mathbf{x}, \mathbf{z}) d\mathbf{z}}{p_\theta(\mathbf{x})} \\ &= \int \textcolor{brown}{p_\theta(\mathbf{z}|\mathbf{x})} \nabla_\theta \log p_\theta(\mathbf{x}, \mathbf{z}) d\mathbf{z}\end{aligned}$$

- $\mathbb{P}_\theta(\mathbf{z}|\mathbf{x})$  performs [credit assignment](#) over latent configurations

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- Joint distribution of a probabilistic model: key quantity of interest, but quite complicated without structural properties
- However, there exist relations of **independence**, **conditional independence** among random variables.
- (Probabilistic) graphical models: Roughly speaking, a graph of random variables.
  - Simple ways to visualize the structure of the model
  - Insights into the structural properties, e.g., conditional independence
  - Computations for inference and learning can be expressed in terms of graphical manipulations

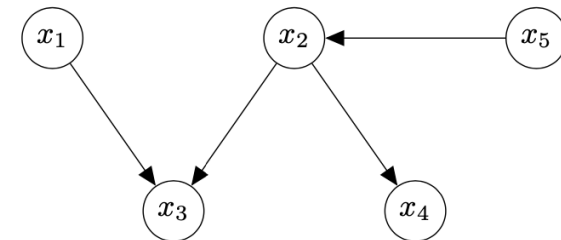
$$\mathbb{P}(a, b, c) = \mathbb{P}(c|a, b)\mathbb{P}(b|a)\mathbb{P}(a)$$



(a) Fully connected.

$$\mathbb{P}(x_1, x_2, x_3, x_4, x_5) =$$

$$\mathbb{P}(x_1)\mathbb{P}(x_5)\mathbb{P}(x_2|x_5)\mathbb{P}(x_3|x_1, x_2)\mathbb{P}(x_4|x_2)$$

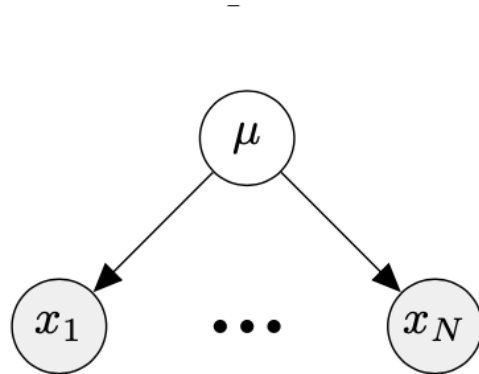


(b) Not fully connected.

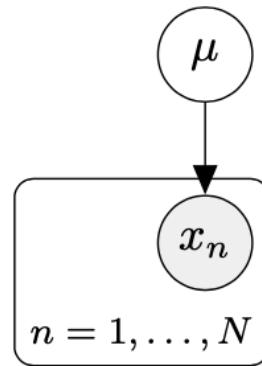
- Nodes: random variables
- Directed edge for direct dependence:  $b$  directly depends on  $a$ :  $a \rightarrow b$
- Graph layout: factorization of the joint distribution

$$\mathbb{P}(x_1, \dots, x_K) = \prod_{k=1}^K \mathbb{P}(x_k \mid \text{Pa}_k), \quad \text{Pa}_k \text{ are the parent nodes of } x_k.$$

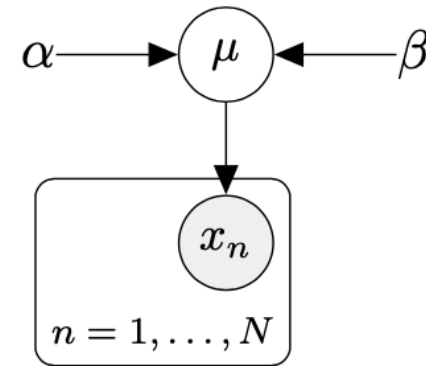
## Example: $N$ coin-flip experiments



(a) Version with  $x_n$  explicit.



(b) Version with plate notation.



(c) Hyperparameters  $\alpha$  and  $\beta$  on the latent  $\mu$ .

- Shaded nodes: observables,  $\mu$ : probability of head, a (latent) random variable
- Joint distribution

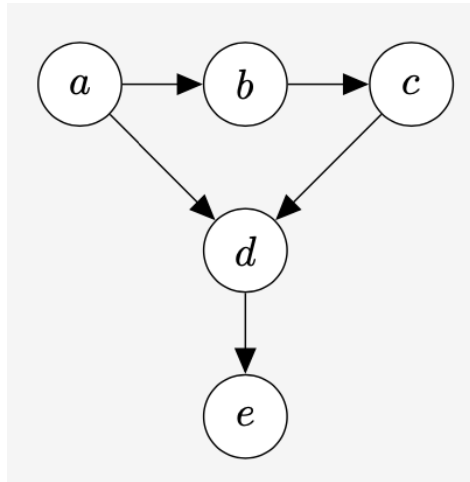
$$\mathbb{P}(x_1, \dots, x_N \mid \mu) = \prod_{n=1}^N \mathbb{P}(x_n \mid \mu)$$

- **Question.** How can we see conditional independence in the directed graphical models? For example,  $\mathcal{A} \perp\!\!\!\perp \mathcal{B} \mid \mathcal{C}$ ?
- $d$ -separation
  - All possible trails<sup>3</sup> from any node  $\mathcal{A}$  to any node in  $\mathcal{B}$
  - Any such path is blocked if it includes any node such that either of the following is true:
    - ▶ The arrows on the path meet either head to tail or tail to tail at the node, and the node is in  $\mathcal{C}$
    - ▶ The arrows meet head to head at the node, and neither the node nor any of its descendants is in  $\mathcal{C}$
  - If all the paths are blocked, then  $\mathcal{A}$  is  $d$ -separated from  $\mathcal{B}$  by  $\mathcal{C}$ .
  - If  $d$ -separated,  $\mathcal{A} \perp\!\!\!\perp \mathcal{B} \mid \mathcal{C}$

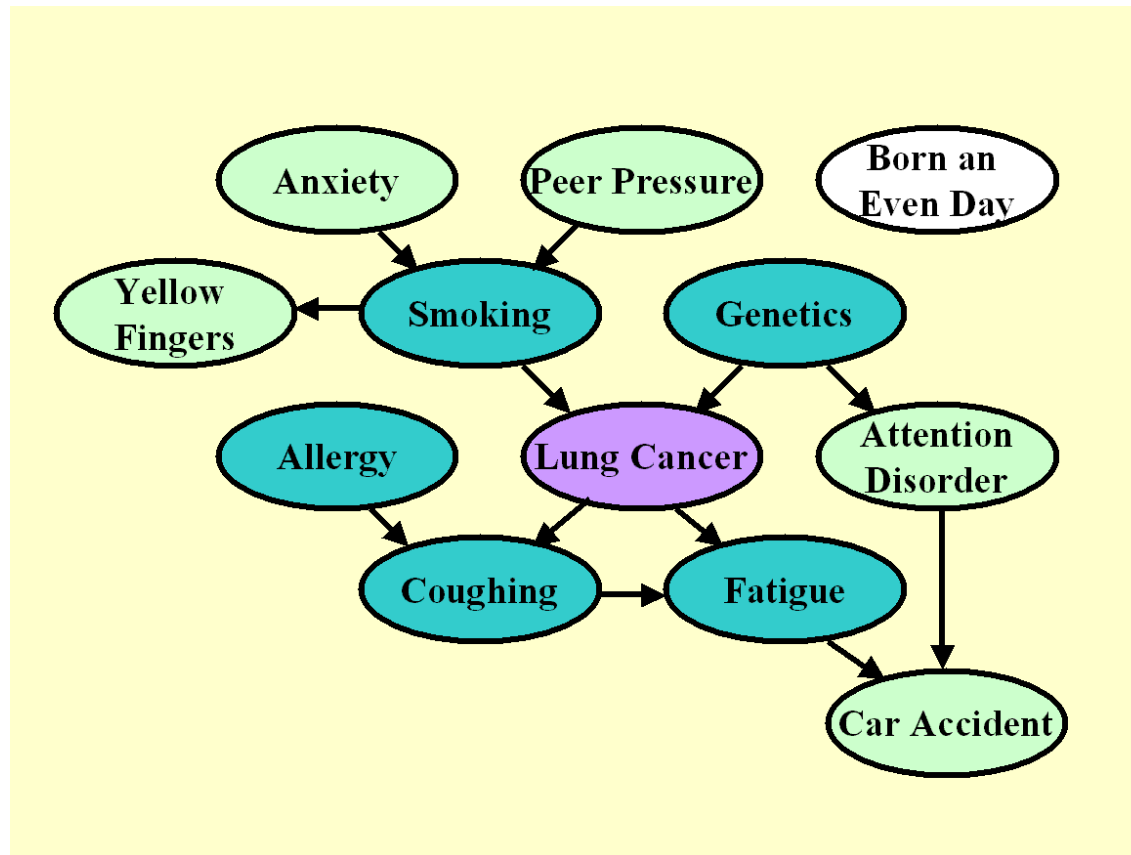
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<sup>3</sup>paths that ignore the direction of the arrows

## Example



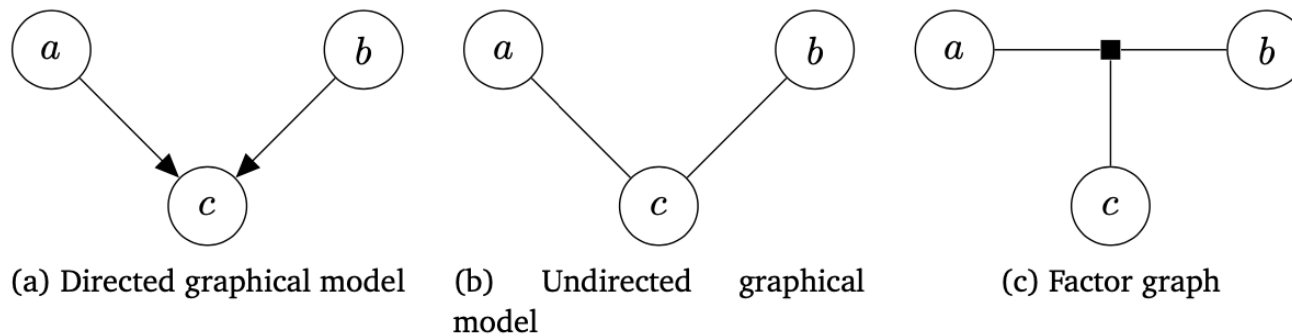
- $b \perp\!\!\!\perp d \mid a, c$
- $a \perp\!\!\!\perp c \mid b$
- $b \not\perp\!\!\!\perp d \mid c$
- $a \not\perp\!\!\!\perp c \mid b, e$



Source: <http://www.causality.inf.ethz.ch/data/LUCAS.html>

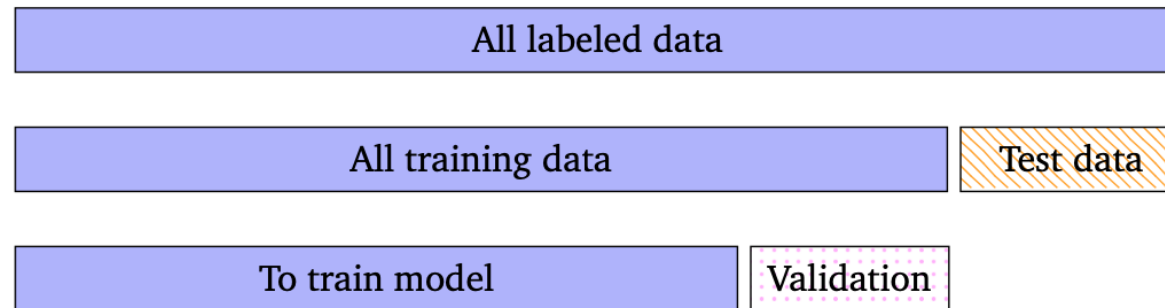


# Three Types of Graphical Models



- Directed graphical models (or Bayesian Networks)
- Undirected graphical models (Markov Random Fields)
- Factor graphs

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- (6) **Model Selection**



- Model selection
  - Tradeoff between model complexity and data fit
  - **Occam's razor.** Find the simplest model that explains the data reasonably well.
- Test set: estimate the generalization performance
- Validation set: choose the best model

- A set of models  $\mathbf{M} = \{M_1, \dots, M_k\}$ , where each  $M_k$  has  $\theta_k$  parameters. A prior  $\mathbb{P}(M)$  on each model  $M \in \mathbf{M}$ .

$$M_k \sim \mathbb{P}(M), \quad \theta_k \sim \mathbb{P}(\theta \mid M_k), \quad \mathcal{D} \sim \mathbb{P}(\mathcal{D} \mid \theta_k)$$

- Posterior distribution  $\mathbb{P}(M_k \mid \mathcal{D}) \propto \mathbb{P}(M_k)\mathbb{P}(\mathcal{D} \mid M_k)$ , where we have the following **model evidence** or **marginal likelihood**:

$$\mathbb{P}(\mathcal{D} \mid M_k) = \int \mathbb{P}(\mathcal{D} \mid \theta_k)\mathbb{P}(\theta_k \mid M_k)d\theta_k \quad (***)$$

- MAP for the model:  $M^* = \arg \max_{M_k} \mathbb{P}(M_k \mid \mathcal{D})$
- With the uniform model prior (i.e.,  $\mathbb{P}(M_k) = 1/k$ ), the MAP estimate equals to maximization of model evidence.

- Compare two probabilistic models  $M_1$  and  $M_2$ :

$$\begin{aligned} \text{(Posterior odds)} = \frac{\mathbb{P}(M_1 | \mathcal{D})}{\mathbb{P}(M_2 | \mathcal{D})} &= \frac{\frac{\mathbb{P}(\mathcal{D}|M_1)\mathbb{P}(M_1)}{\mathbb{P}(\mathcal{D})}}{\frac{\mathbb{P}(\mathcal{D}|M_2)\mathbb{P}(M_2)}{\mathbb{P}(\mathcal{D})}} = \underbrace{\frac{\mathbb{P}(M_1)}{\mathbb{P}(M_2)}}_{\text{Prior odds}} \underbrace{\frac{\mathbb{P}(\mathcal{D} | M_1)}{\mathbb{P}(\mathcal{D} | M_2)}}_{\text{Bayes factor}} \end{aligned}$$

- $\mathbb{P}(\mathcal{D} | M_k)$ : How well the data is predicted by the model  $M_k$
- With the uniform model prior, the prior odds = 1
- Computation of Bayes factor requires the complex integration (\*\*\*) in the previous slide. In this case, we rely on some approximations such as MCMC (Markov Chain Monte Carlo).

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Questions?

1)