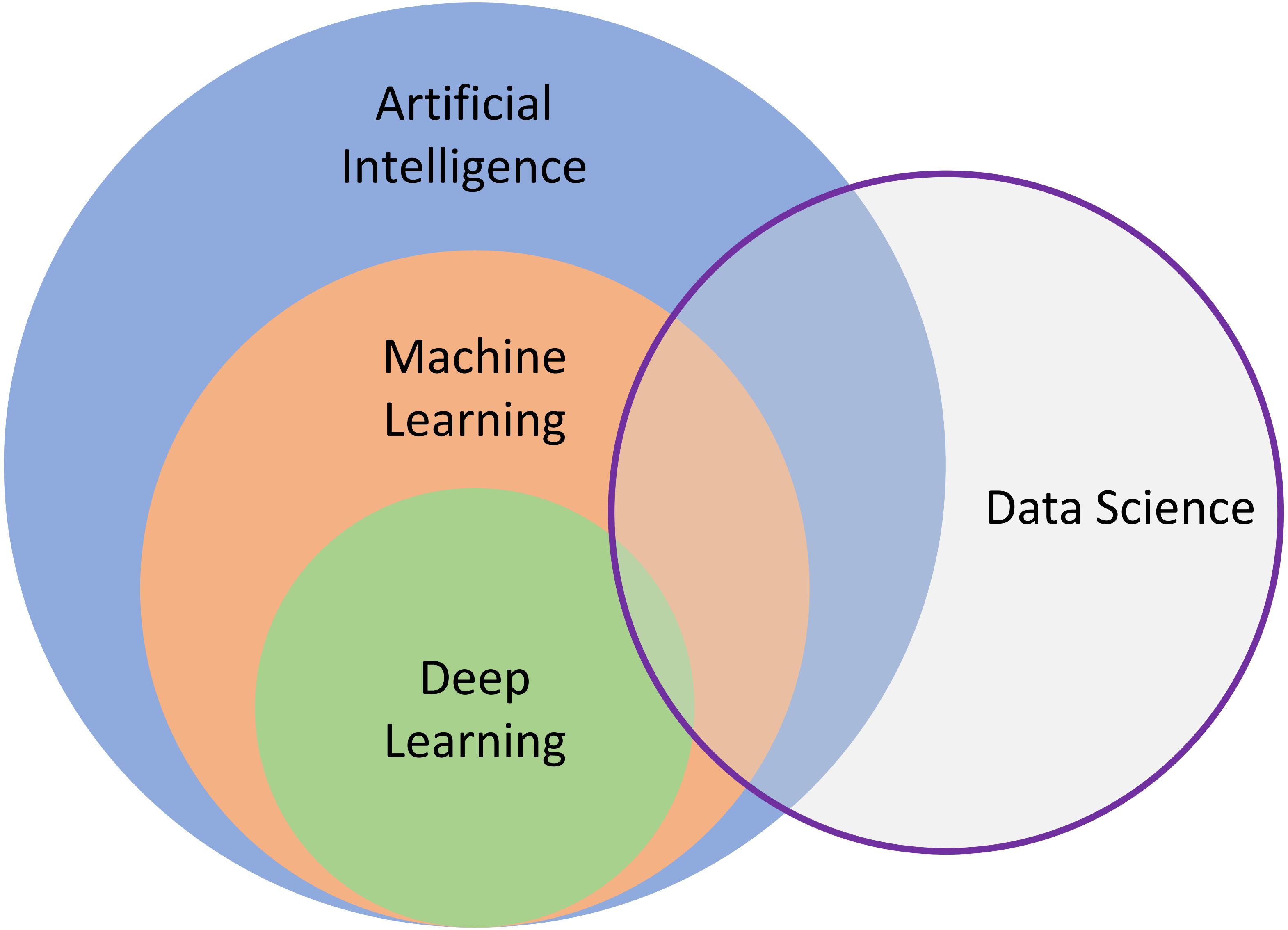
BI and AI

Demand Forecasting, Replenishment, Dynamic Pricing

June 2023



Deep Learning:

special kind of ML algorithms using (deep) neural networks

BI / Data Science:

extract knowledge from data (by means of ML, among other things)

Automated Decision Making with AI in Retail

replenishment

avoid waste or out-of-stock situations (lost sales)

pricing

shape demand to maximize of revenue or profit

typically thousands of products and stores:
many individual decisions → **automation crucial**

decisions under uncertainty (random variables, many influencing factors)
difficult for humans → **statistical methods**

Demand-Driven Decision Making

core component: demand forecasting

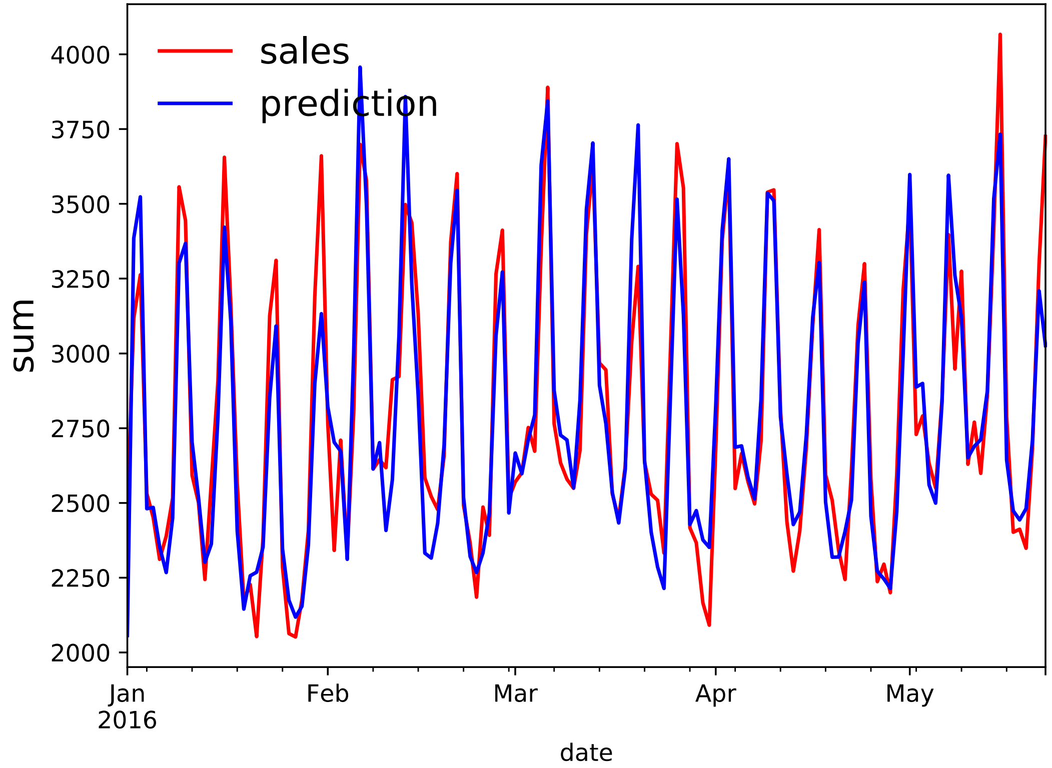
used in subsequent (or entangled) decision making

- ordering / replenishment: minimization of costs for over- or under-fulfillment of demand

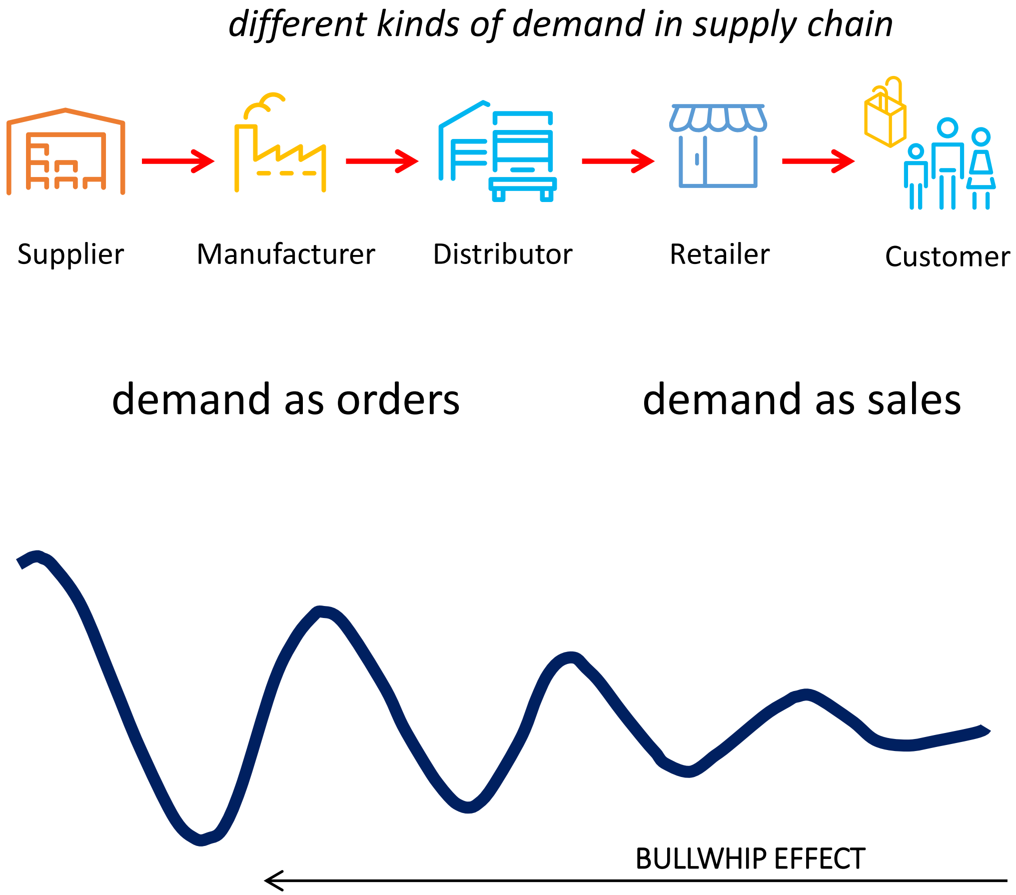
- dynamic pricing: shape demand by altering its causes

(other possibility: individual customer targeting)

Demand in Supply Chains

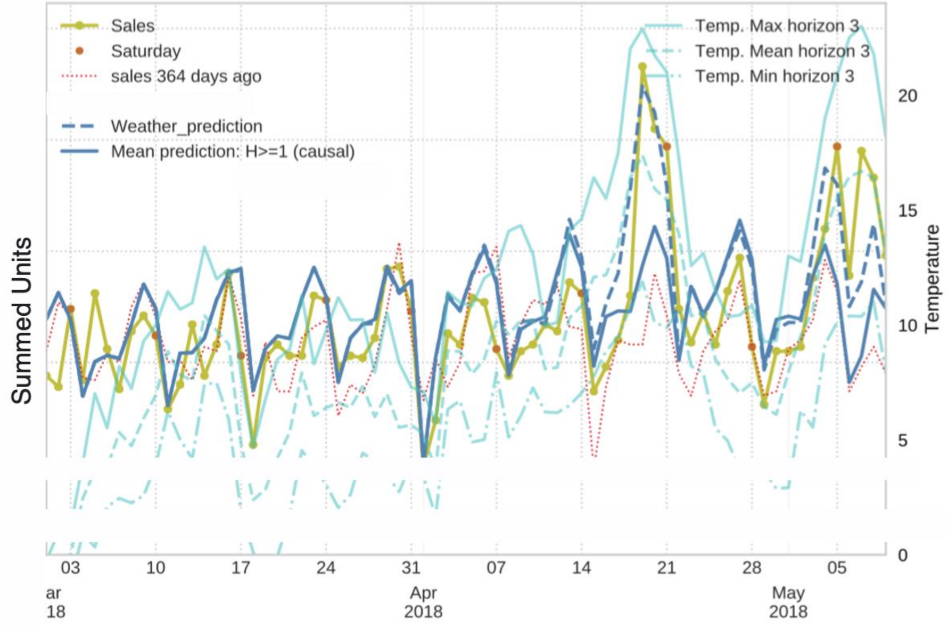


demand is a time-tagged random variable → time series regression

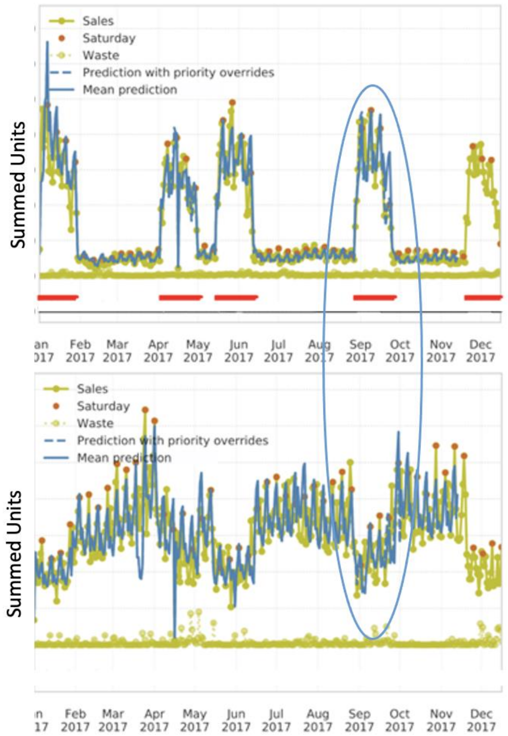


Demand in Retail

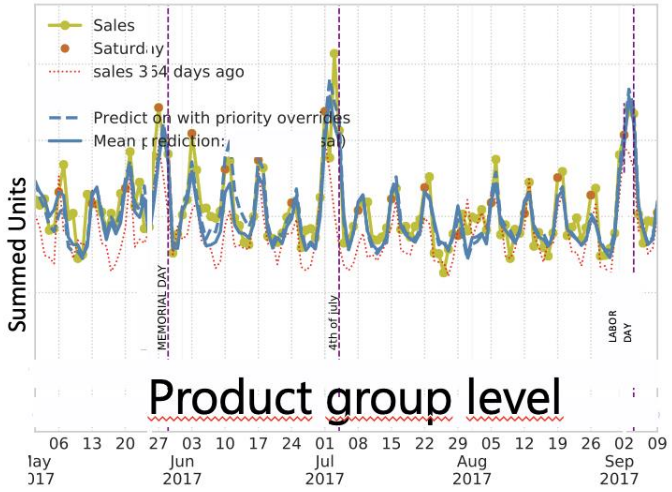
Summer Weather



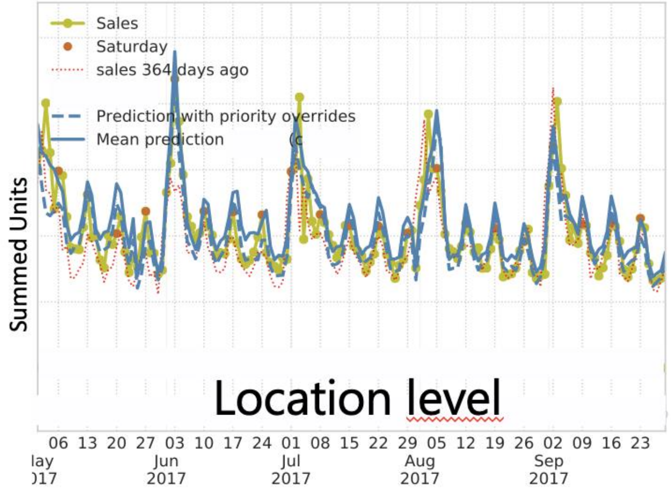
Cannibalization



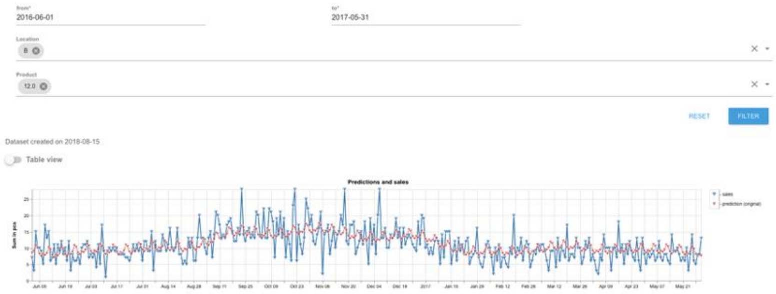
Events



Payday Effect



Seasonality



Time Series Modeling

Types of Time Series Forecasting Information

auto-correlation

- using past values of considered time series as function of lag
- identifying periodicity (seasonality) and trend

exogenous variables

- using correlations of other variables to considered time series
- examples in demand forecasting: price, weather
- such effects lasting for some time create spurious auto-correlation

Traditional Forecasting Methods

direct use of auto-correlation:

- exponential smoothing
  - e.g., exponentially weighted moving average (EWMA): $\hat{y}_t = \alpha \cdot y_{t-1} + (1-\alpha) \cdot \hat{y}_{t-1}$
  - potentially grouped by important lag like day of week or exogenous variables like promotion
- in general: (S)AR(I)MA(X)
- largely univariate time series models
- multivariate model by stacking: include univariate forecasts (e.g., EWMA) as feature in ML method

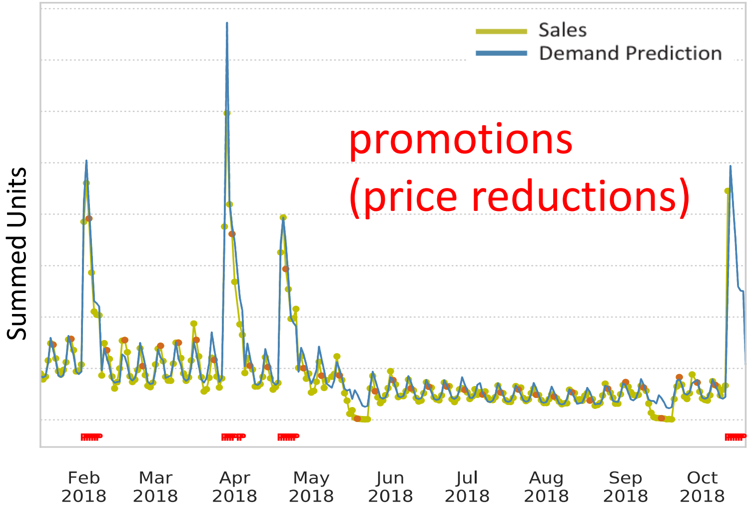
decomposition-based approaches:

- additive components: trend, seasonality, holidays, others
- curve fitting (ML-like)
- Generalized Additive Models (e.g., multiplicative effects)
- example method: prophet
- natural way for multivariate model: training with several independent time series, distinguished by additional feature (e.g., product ID)

Demand Forecasting with ML

many individual time series to consider

typical retail grocery chain:
- products (items): ~20k
- locations (stores): ~500
- daily/hourly aggregated sales



advantages of ML over traditional univariate time series forecasting:

combined learning on all time series of product-location combinations (rather than separately optimizing individual time series)
→ **reduces variance** by exploiting commonalities

natural consideration of many exogenous variables (prices, promotions, holidays, weather, ...)
→ **reduces bias**

to be noted:
- categorical features important (products and locations → high cardinality)
- mainly multiplicative effects
- demand (approximately) following Poisson (or rather negative binomial) distribution

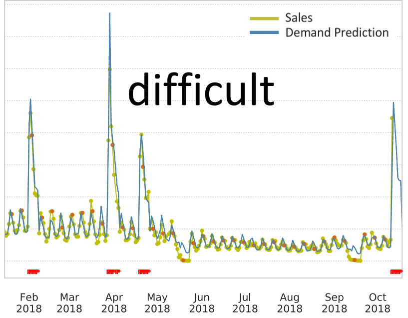
Beware of (Spurious) Auto-Correlation

Most forecasting methods rely on lagged target information.

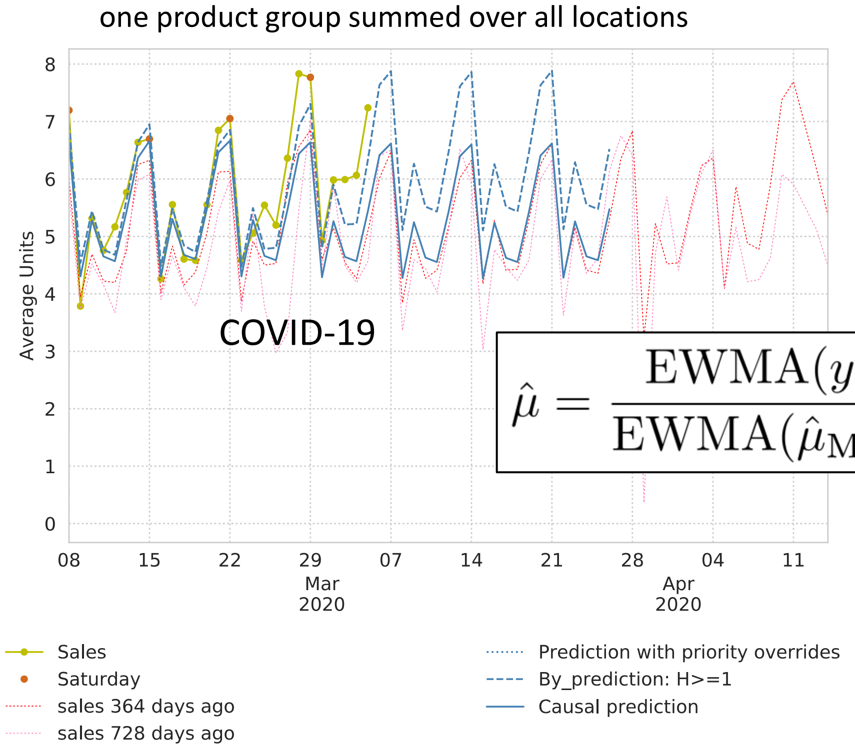
- univariate time series methods
- exponential smoothing features in ML model
- sequence modeling in deep learning (e.g., recurrent neural networks)

However, this makes learning of exogenous effects much harder.

- already blended in target auto-correlation
- delayed effects of short-lived structures/trends



➢ simple solution: no use of target auto-correlation in ML model (but subsequent residual correction to capture missing trends)

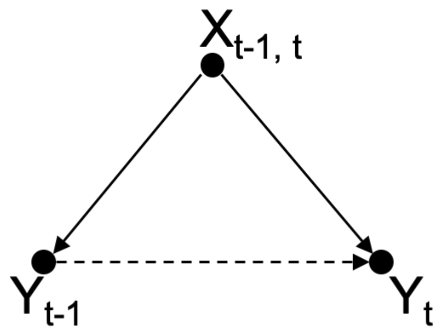


$$\hat{\mu} = \frac{\mathrm{EWMA}(y)}{\mathrm{EWMA}(\hat{\mu}_{\mathrm{ML}})} \cdot \hat{\mu}_{\mathrm{ML}}$$

Temporal Confounding

auto-correlation often only spurious: common causes at consecutive times

→ no direct causal effects



advantages of learning direct causal effects from exogenous information instead of confounded auto-correlation:

- explainability
- long-term forecasting
- predictability of rare events

Quick Introduction to ML

MACHINE LEARNING

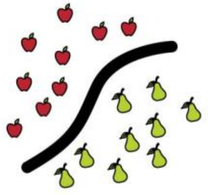
training target available (labeled or past data)

data not labeled in any way

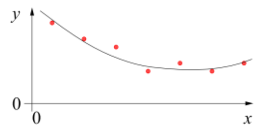
no supervision, but goal-based interaction with environment

SUPERVISED

CLASSIFICATION



REGRESSION

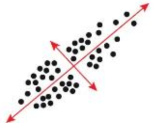


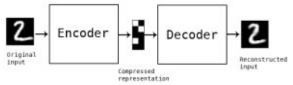
UNSUPERVISED

CLUSTERING

ASSOCIATION

DIMENSIONALITY REDUCTION





REINFORCEMENT LEARNING

LEARN STATE OR ACTION VALUES

LEARN POLICY DIRECTLY

learning by teacher
(high-dimensional curve fitting)

learning by observation
(pattern recognition)

learning by trial-and-error
(sequential decision making)

... **ML** ...

Supervised Learning Scenario

ML domain:
no deterministic dependencies between input and output

map inputs to output: $y = f(\boldsymbol{x})$ (estimated: $\hat{f}(\boldsymbol{x})$)

random variables Y and $\boldsymbol{X} = (X_1, X_2, \cdots, X_p)$ usually many dimensions

fit train data set of $(y_i, \boldsymbol{x}_i)$ pairs

(i.i.d. assumption: random samples from underlying data-generating process)

then apply learned statistical dependencies to test data set

classification:

categorical target: $y = 0$ or $y = 1$ (e.g., image of cat or not), predict probabilities

regression:

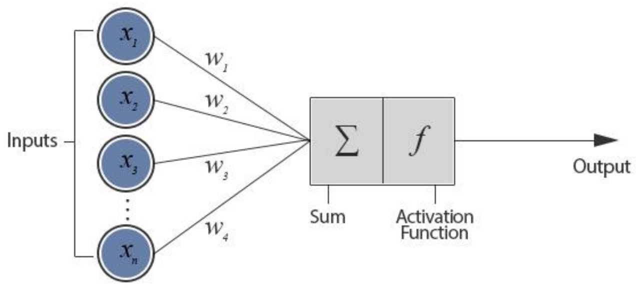
real-valued target: $Y \in [0, \infty)$ (e.g., demand forecasting) or $Y \in (-\infty, \infty)$

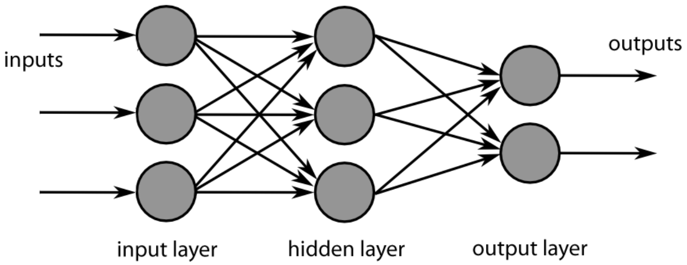
Algorithmic Families

linear (parametric) models

- linear regression
- Generalized Linear Models
- Generalized Additive Models

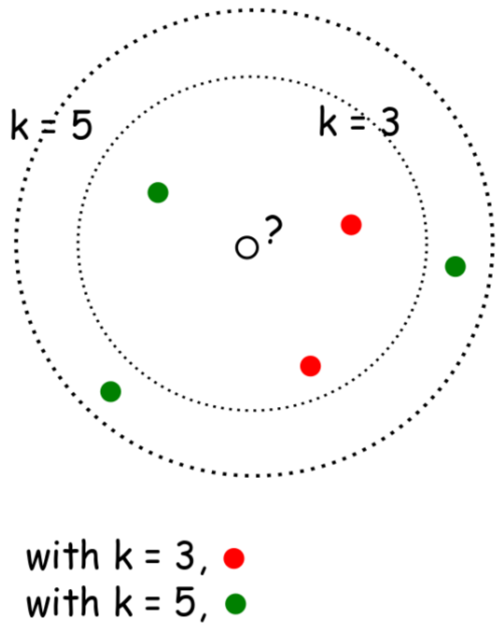
neural networks: non-linear just by means of activation functions





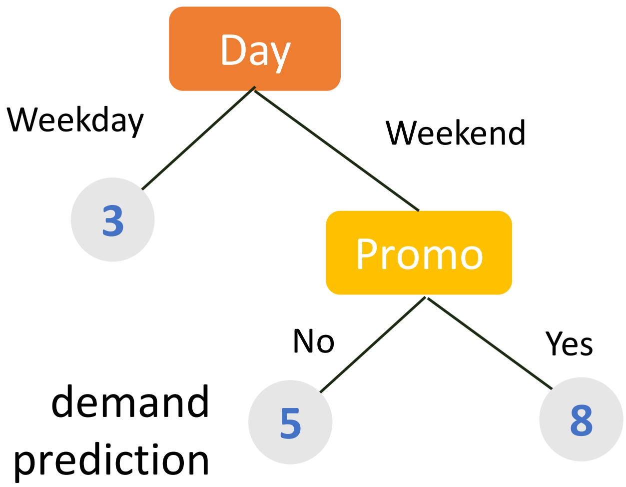
from wikipedia

nearest neighbors (local methods, instance-based learning) – non-parametric models



kernel/support-vector machines: linear model (maximum-margin hyperplane) with kernel trick

decision trees

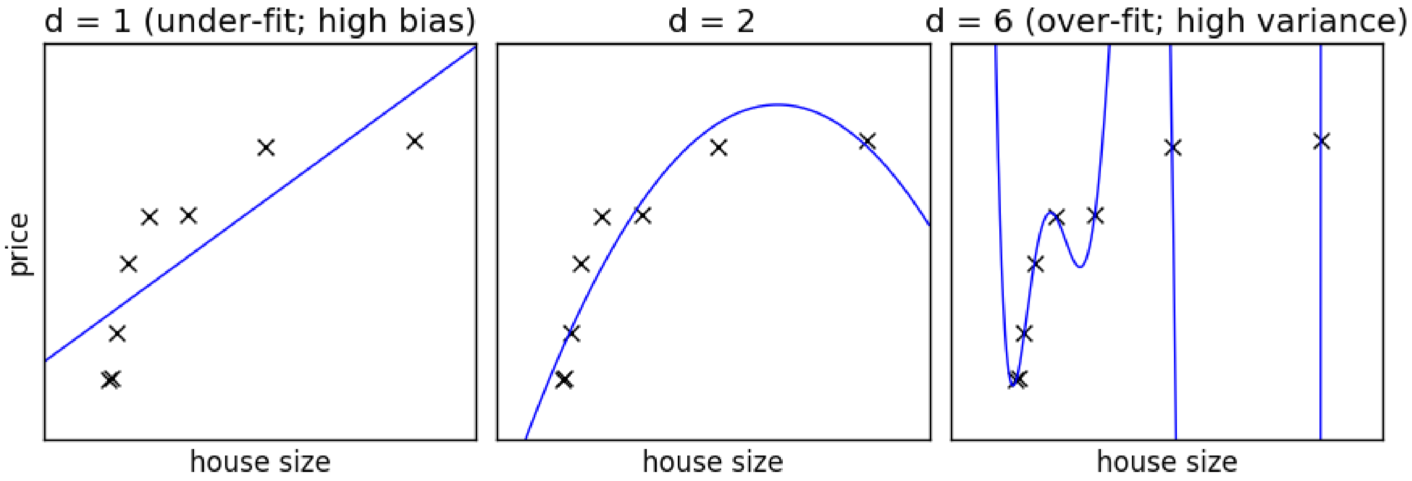


often used in ensemble methods

- bagging: random forests
- boosting: gradient boosting

Common Core of Statistical Learning

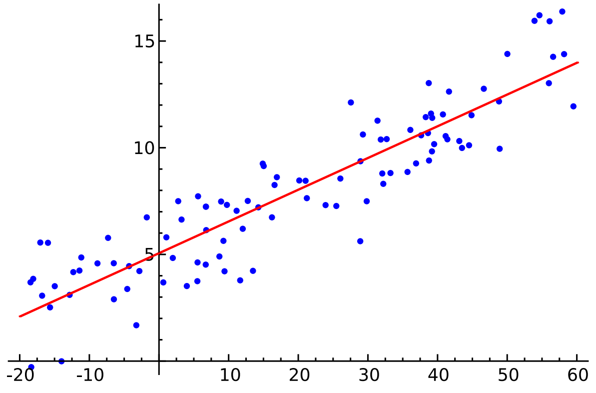
curve fitting (e.g., maximum likelihood estimation)
through **optimization** methods (e.g., gradient descent)
with the aim of **generalization** (by means of **regularization** techniques)



from scikit-learn documentation

At its heart, all the diverse statistical learning methods are reflections of the same underlying concept, and just differ in their applicability for different use cases.

Count Data & Multiplicative Effects: Generalized Linear Models



from wikipedia

Linear Regression

fit:

$$y_i = \overbrace{\hat{\alpha} + \sum_{j=1}^{p} \hat{\beta}_j \, x_{ij}}^{\hat{f}(\boldsymbol{x}_i)} + \varepsilon_i$$

(model)

error term (noise): reflects assumed data distribution (here: Gaussian with same variance σ^2 for all samples)

parameters to be estimated:

- $\hat{\alpha}, \hat{\boldsymbol{\beta}}$

→ $\hat{\sigma}^2 = \frac{1}{n} \sum_{i=1}^{n} \left(y_i - \hat{f}(\boldsymbol{x}_i) \right)^2$

(approximating assumed true $\alpha, \boldsymbol{\beta}$, σ)

predict:

$$\hat{y}_i = E[Y | \boldsymbol{X} = \boldsymbol{x}_i] = \hat{f}(\boldsymbol{x}_i)$$

- conditional mean for squared loss of least squares method
- predict arbitrary quantile by means of quantile loss

$$p(y | \boldsymbol{x}_i) = \mathcal{N}(y; \hat{y}_i, \hat{\sigma}^2)$$

Gaussian

mean

variance (reflected by ε_i in fit)

Multiplicative Model

- count data: $Y \in [0, \infty)$
- Y follows Poisson (or negative binomial / Poisson-gamma) distribution

log-linear model (Gaussian errors in fit, Poisson with mean $\hat{y}_i$ predicted):

single parameter

$$\log(\underbrace{E[Y|\boldsymbol{X} = \boldsymbol{x}_i]}_{\hat{y}_i}) = \hat{\alpha} + \sum_{j=1}^{p} \hat{\beta}_j \, x_{ij}$$

link function

- further advantage: usually multiplicative effects for count data, i.e., variation proportional to level (small effects for small counts, large effects for large counts)

Sidenote: Classification by Logistic Regression

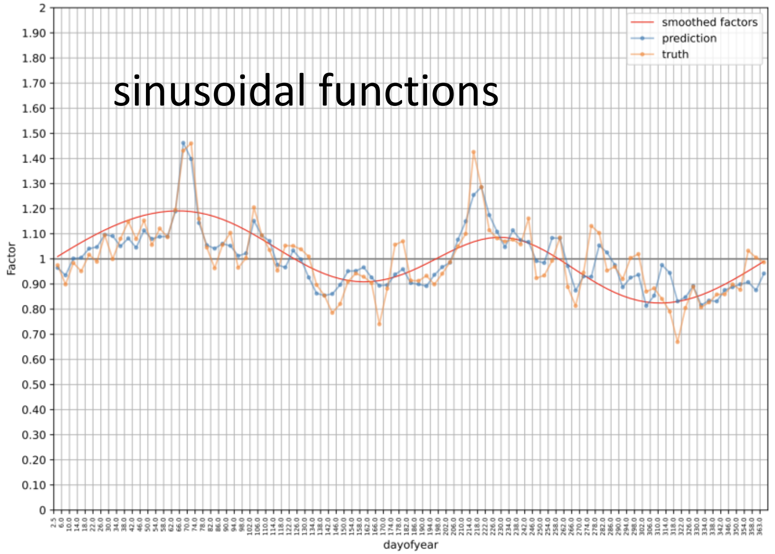
- predict probability p_i for $y = 1$ respectively $y = 0$ for each sample
- link function: logit (log-odds)
- Y following Bernoulli distribution

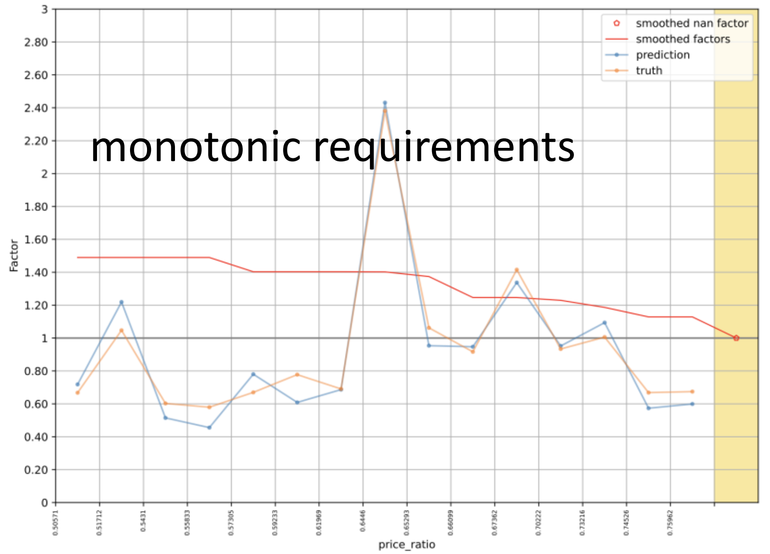
$$\operatorname{logit}(E[Y|\boldsymbol{X} = \boldsymbol{x}_i]) = \ln\left(\frac{p_i}{1 - p_i}\right)$$

$$= \hat{\alpha} + \sum_{j=1}^{p} \hat{\beta}_j \, x_{ij}$$

Generalized Additive Models

[Cyclic Boosting](#)





blending of Generalized Linear Models and additive models

$$g(E[Y|\boldsymbol{X} = \boldsymbol{x}_i]) = \hat{\alpha} + \sum_{j=1}^{p} \hat{h}_j(x_{ij})$$

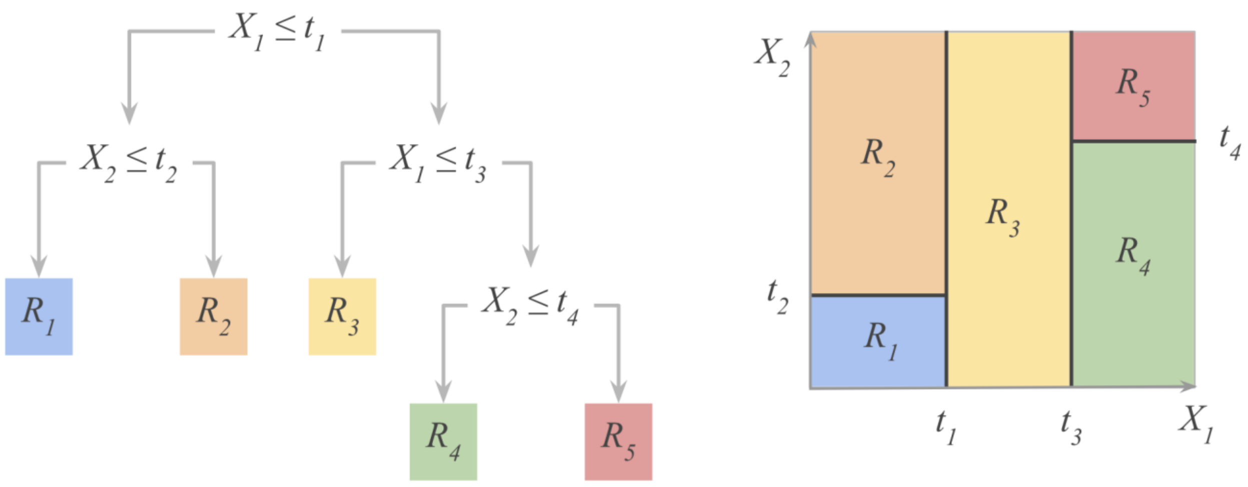
smooth functions

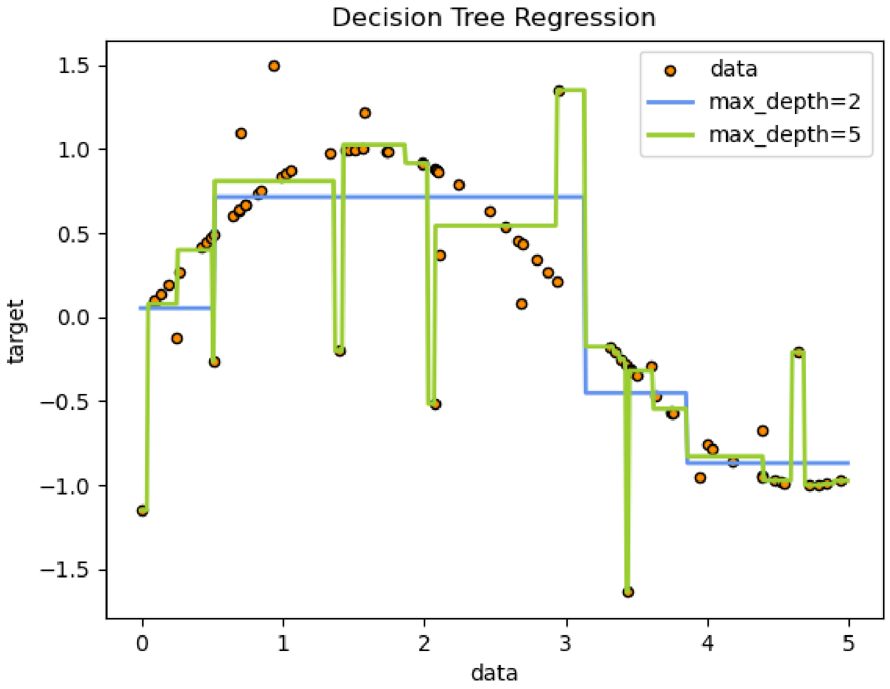
- potentially non-parametric form
- describe non-linear effects
- estimated, e.g., via backfitting algorithm
- extension: add interaction terms between different features (e.g., different holiday effects for different products)

Automatic Interaction Learning: Gradient Boosting

Decision Trees

- non-parametric learning of simple decision rules
- usually, binary trees
- axis-parallel decision boundaries (box-shaped regions in feature space)
- fit constant $\hat{c}$ in each box (note similarity to kNN)
  - classification: majority class of target
  - regression: average of target
- fully explainable models





from scikit-learn

Decision Tree Learning

finding optimal partitions R by overall loss minimization computationally infeasible → recursive partitioning of data (greedy algorithm)

for each binary partition into regions R_1 and R_2, decisions on splitting variable j and split point s by minimizing impurity functions I (weighted by number of observations N in child nodes):

$$R_1(j,s) = \{\boldsymbol{x}|x_j \leq s\} \qquad \text{and} \qquad R_2(j,s) = \{\boldsymbol{x}|x_j > s\}$$

$$\mathrm{argmin}_{j,s}\left[\frac{N_{R_1}}{N}\,\mathrm{argmin}_{\hat{c}_1}\left(I_{R_1}\right) + \frac{N_{R_2}}{N}\,\mathrm{argmin}_{\hat{c}_2}\left(I_{R_2}\right)\right]$$

recursively for each node in tree

regression:

$I_{R_1} = \sum_{x_i \in R_1(j,s)} (y_i - \hat{c}_1)^2$ → $\mathrm{argmin}_{\hat{c}_1}\left(I_{R_1}\right)$ solved by $\hat{c}_1 = \bar{y}_{R_1}$

for $\mathrm{argmin}_{j,s}$, choose boxes to make target averages in each box as different as possible

Boosting

idea: sequentially learn and combine several "weak" learners (such as small decision trees, but in principle any ML algorithm) to construct a "strong" one

→ gradually (in a greedy fashion) reducing bias of ensemble model

in simple terms: building a model from the training data, then creating a second model that attempts to correct the errors from the first model, …

→ each subsequent weak learner is forced to concentrate on the examples that are missed by the previous ones in the sequence

not a committee of models

typically, use simple, high-bias methods as individual models

Gradient Boosting

forward stagewise additive modeling:

1. initialize $\hat{f}_0(\boldsymbol{x}) = 0$
2. for $m = 1$ to M
   a) compute $\underset{\hat{h}_m}{\operatorname{argmin}} \sum_{i=1}^{N} L\left(y_i, \hat{f}_{m-1}(\boldsymbol{x}_i) + \hat{h}_m(\boldsymbol{x})\right)$
   b) set $\hat{f}_m(\boldsymbol{x}) = \hat{f}_{m-1}(\boldsymbol{x}) + \hat{h}_m(\boldsymbol{x})$

$$\approx L\left(y_i, \hat{f}_{m-1}(\boldsymbol{x}_i)\right) + \hat{h}_m(\boldsymbol{x}_i) \left[\frac{\partial L\left(y_i, \hat{f}(\boldsymbol{x}_i)\right)}{\partial \hat{f}(\boldsymbol{x}_i)}\right]_{\hat{f}=\hat{f}_{m-1}}$$

→ functional gradient descent

prominent implementations:

- XGBoost: uses second-order Taylor approximation in loss function (Newton-Raphson instead of gradient descent)
- LGBM: uses improved histogram-based algorithm
- CatBoost: uses kind of leave-one-out encoding for categorical features

Decision Tree Sizes for Boosting

consider degree to which features interact with each other in given data set (see ANOVA expansion)

- decision trees with single split (aka decision stumps): covering no interaction effects, just main effects of individual features
- decision trees with two splits: covering second-order interactions
- decision trees with three splits: covering third-order interactions

(usually interaction order not much higher than $\sim$5)

why boosting often works better than single large, low-bias model: uncorrelated learners, each focusing on a specific aspect of the data

Embeddings & Feature Learning: Deep Learning

Categorical Variables

tabular data usually heterogenous, often with sparse categorical variables (like color of an object)

→ need for an encoding for categorical variables

different possibilities:

- ordinal encoding
- leave-one-out encoding (use mean of target for given category excluding current row)
- one-hot encoding (suffers from curse of dimensionality)
- embeddings

stacking:

```
X.sort_values(['date’])
.groupby(['store','item'])['y’]
.apply(lambda x: x.shift(3)
.ewm(alpha=0.15).mean())
```

prediction horizon

Embeddings

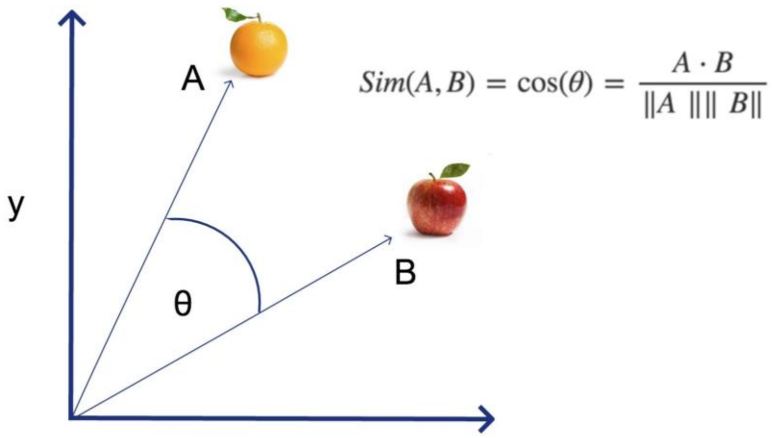
representation of entities by vectors

similarity between embeddings by, e.g., cosine similarity → semantic similarity

most famous application: word embeddings → associations (natural language processing)

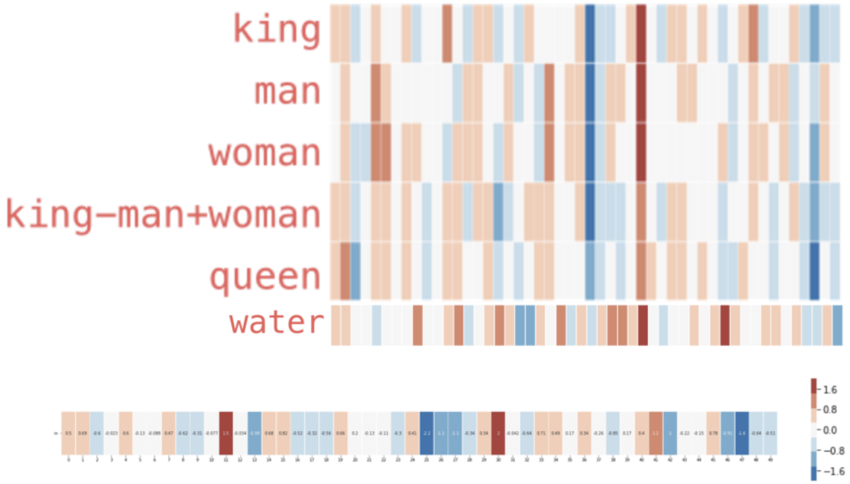
but general concept: embeddings of (categorical) features (e.g., products in recommendation engines)

end-to-end learning: embeddings layer in deep neural network, e.g., multi-layer perceptron (MLP)



but also direction of difference vectors interesting (analogies):

king − man + woman ~= queen



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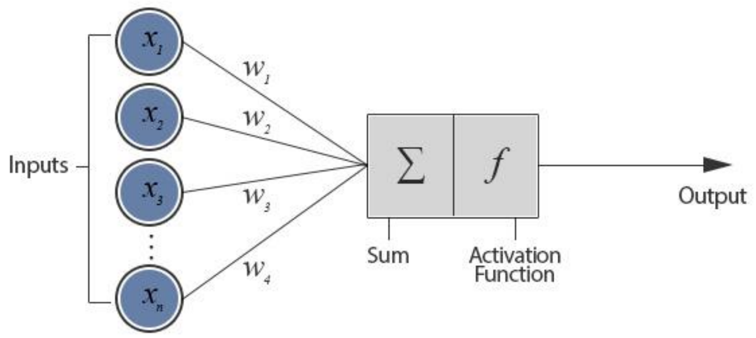
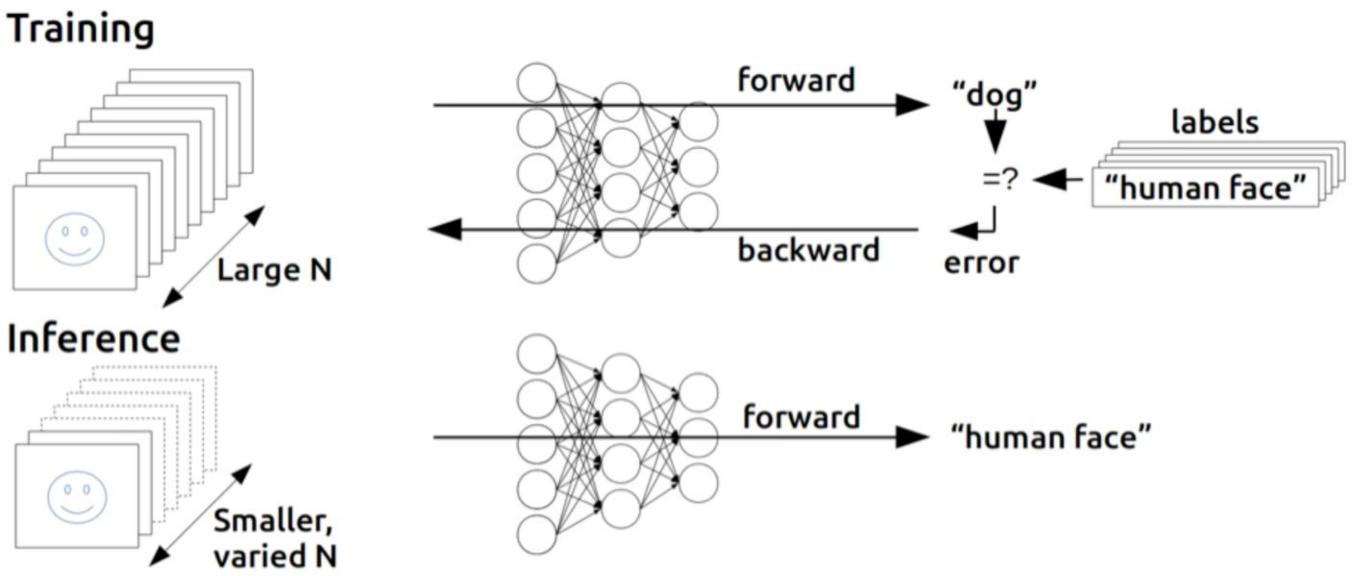
(Deep) Neural Networks



back-propagation of errors (gradients of cost function according to weights) through layers via chain rule of calculus (avoiding redundant calculations of intermediate terms)

each node exchanges information only with directly connected nodes → enables efficient, parallel computation



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- forward pass: current weights fixed, predictions computed
- backward pass: errors computed from predictions and back-propagated → weights then updated according to loss gradients (via gradient descent)

Examples for Feature Engineering

seasonality

day of week, payday, week of year

weather

event-like: first sunny weekend, snowstorm, …

events (e.g., holidays)

time window around event (e.g., monotonic)

promotion

days since start of promotion period

price

ratio of reduced and normal price, price-demand elasticity

product information

text (name/description) or image embeddings

Feature Engineering vs Feature Learning

shallow learning:

representation encoded in features

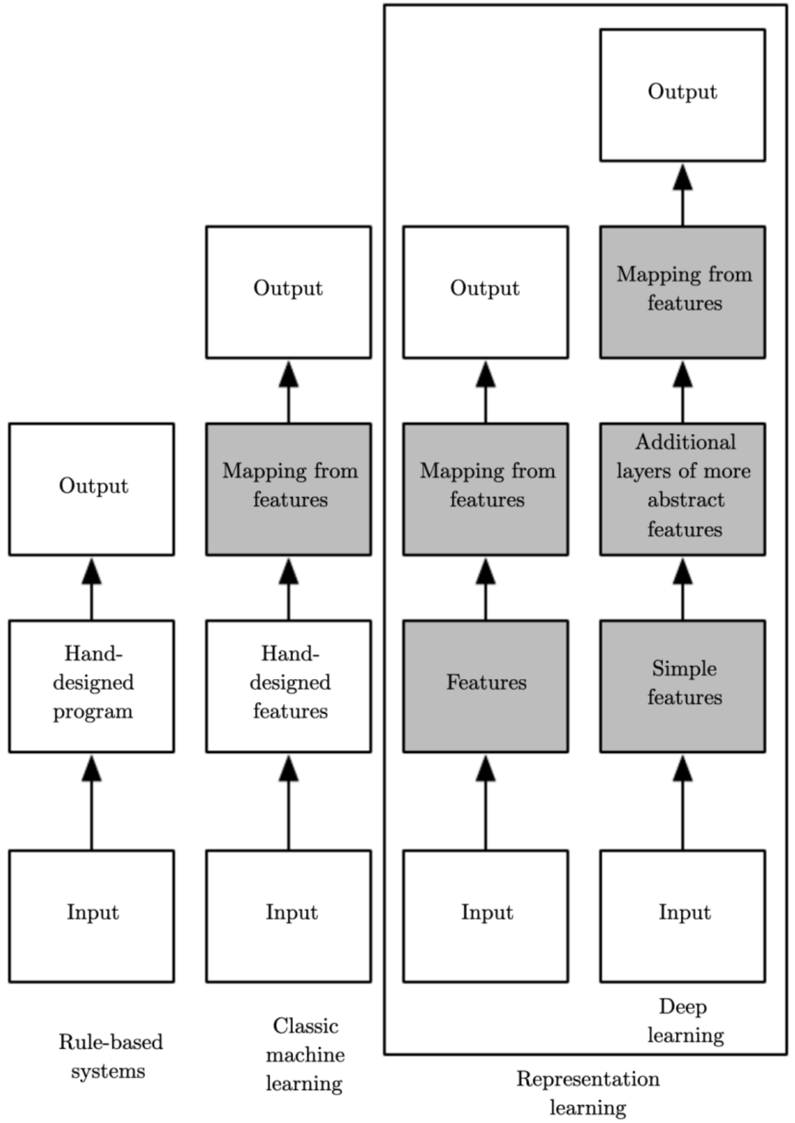
→ feature engineering

deep learning:

representation encoded in network

→ feature/representation learning

(hierarchy of concepts learned from raw data in deep graph with many layers)



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Tabular vs Unstructured Data

deep learning methods dominate applications on unstructured data (like text or images), but not necessarily on tabular data

typical characteristics of tabular data difficult to handle for deep learning:

- irregular patterns in target function (neural networks require piecewise continuous targets)
- uninformative features
- non-rotationally invariant data (linear combinations of features misrepresent the information)

tree-based models (e.g., gradient boosting) can naturally deal with these situations

Black-Box Models

To build trust in AI systems, individual predictions/actions need to be fully transparent, i.e., explainable.

(do not confuse explainability with causality though)

Unfortunately, complex models like deep learning methods are difficult to interpret.

→ need for model-agnostic methods to explain black-box models

examples: local surrogates (LIME), Shapley values (SHAP)

overview

Deep Learning Methods for Sequential Data

→ direct inclusion of auto-correlation in ML model (but remember: mainly spurious)

convolutional neural networks (CNN)

- main application computer vision: images correspond to regular 2D grids of data (pixels)
- time series data as 1D grid at regular time intervals

- parameter sharing via convolutions (and pooling) → highly regularized feed-forward networks
- fixed time window (kernel)

- multivariate time series model via different input channels

recurrent neural networks (RNN)

- main application natural language processing (NLP): sequence of words (tokens)
- time series data as time-tagged stream

- parameter sharing via recurrent nodes → context-awareness (input from past activations)
- variable-length time series

- multivariate time series model via more input nodes

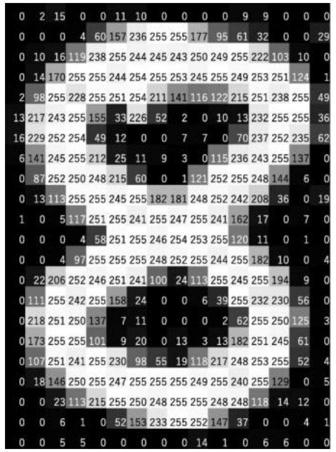
transformers

- main application NLP (largely replaced RNNs), but also computer vision
- time series data as directed graph (attention in edges)

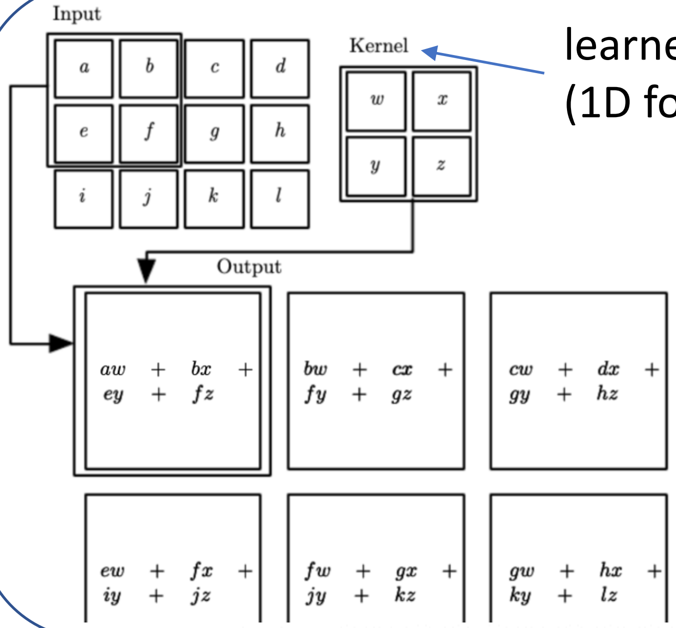
- masked self-attention to focus on relevant past time steps and positional encoding to include order of sequence

- multivariate time series model via input concatenation

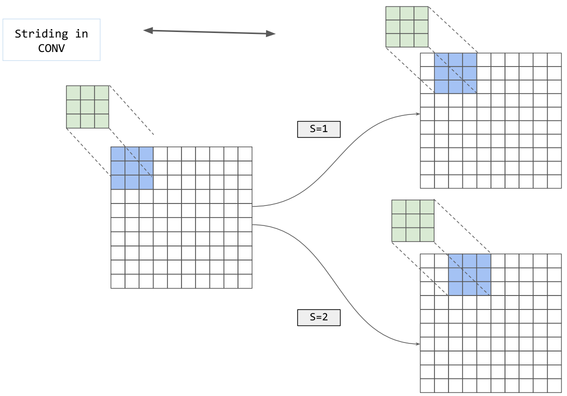
CNN



1D for time series



learned parameters (1D for time series)



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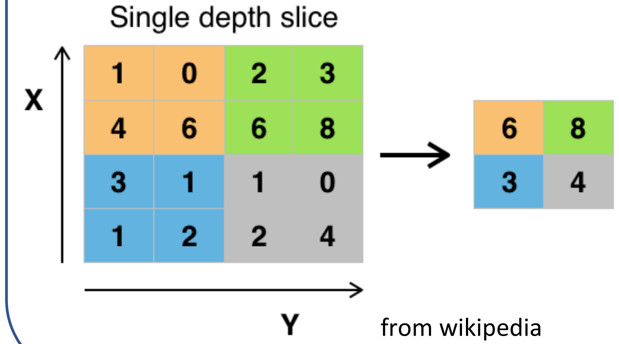
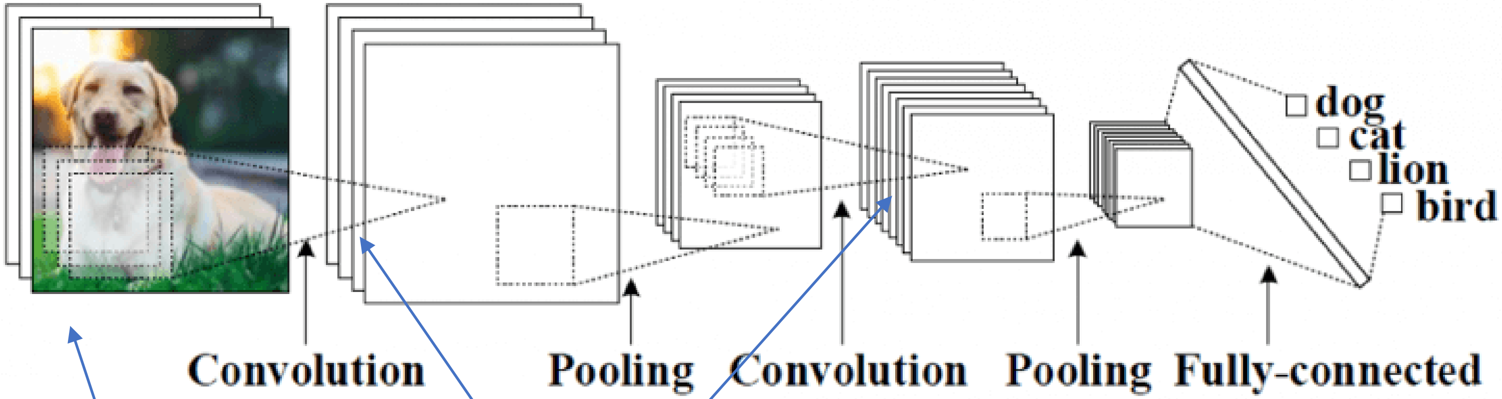
max pooling:



from wikipedia

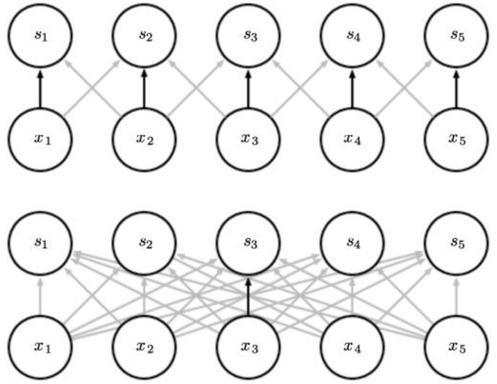


many images (training examples), potentially with several channels

several kernels producing several feature maps

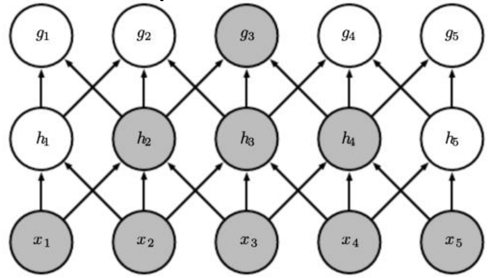
down-sampling by convolutions and pooling

convolutional vs fully-connected layer:



source

receptive fields:



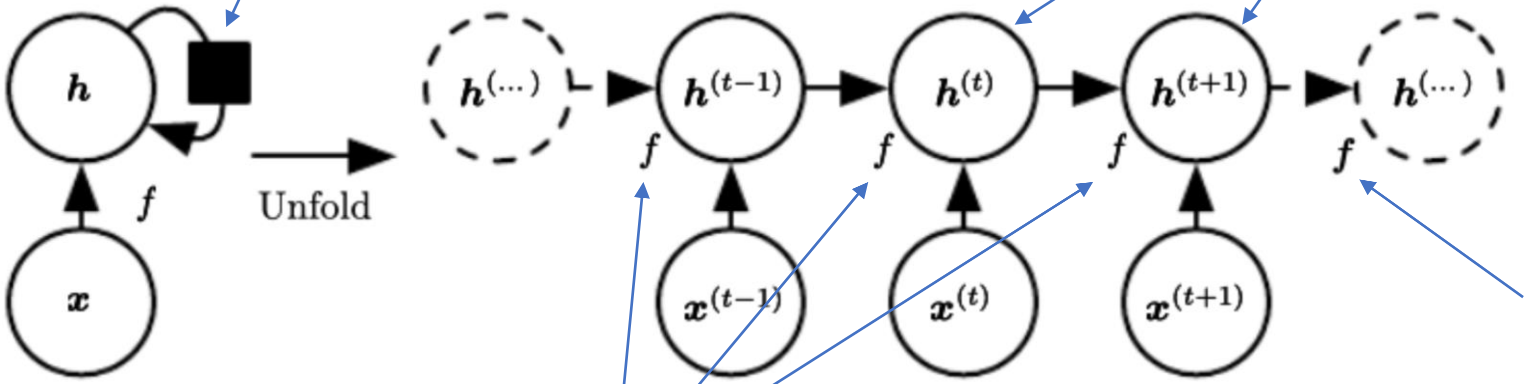
RNN: Back-Propagation through Time

activation of recurrent
nodes at that point in time

interaction with delay
of single time step

computational graph with repeated pieces:

hidden layer: several
recurrent neurons



single model operating
on all time steps

input layer:
- NLP: one-hot encoded words or embeddings
- time series: lagged target (e.g., sales) or exogenous time series (e.g., price)

source

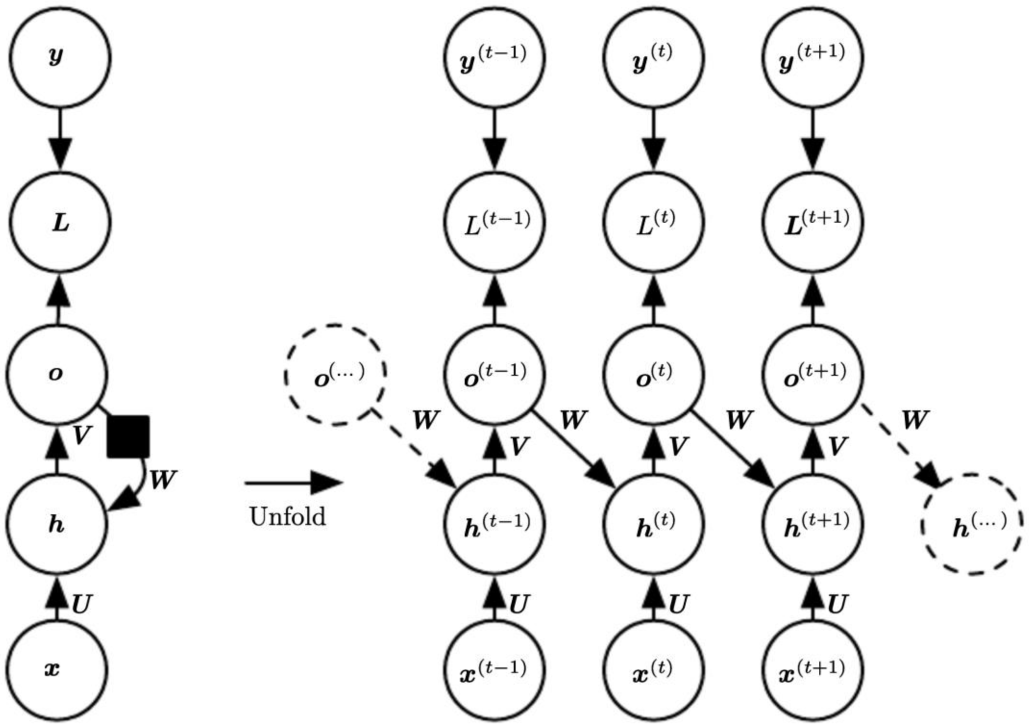
parameter/weight
sharing over time

Teacher Forcing

instead of feeding model output back into itself, use target values directly for feedback from output to hidden layer

example demand forecasting: sales from day before (different to usage as input from last slide)

e.g., RNN:



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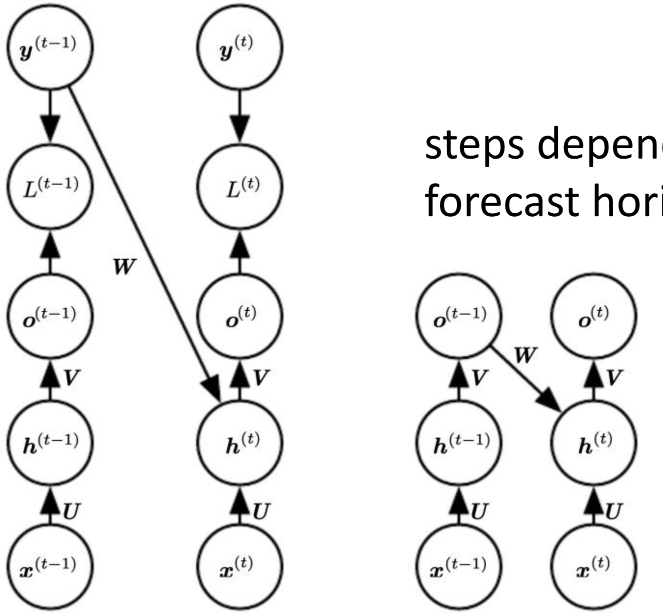
steps depend on forecast horizon



Train time

Test time

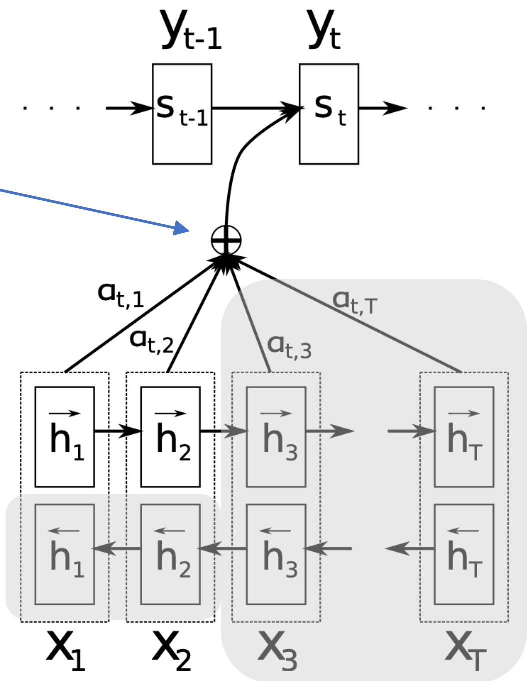
Transformer

attention:

$$c_i = \sum_{j=1}^{T_x} \alpha_{ij} h_j$$

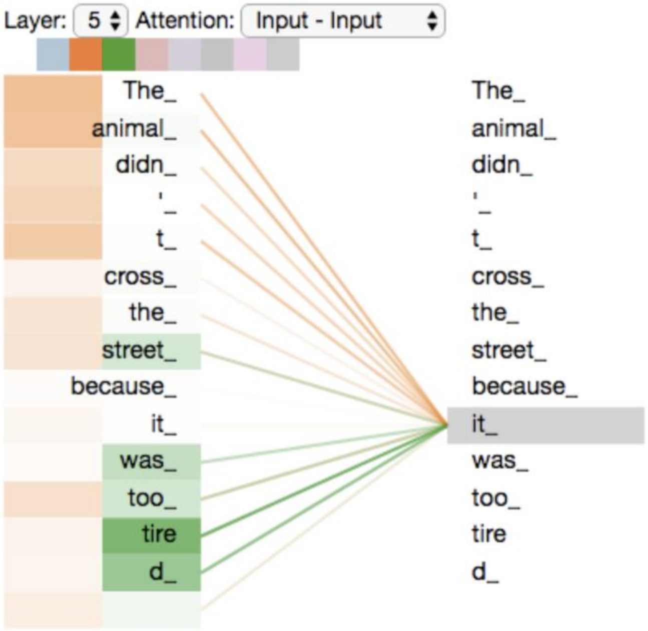
$$\alpha_{ij} = \frac{\exp\left(e_{ij}\right)}{\sum_{k=1}^{T_x} \exp\left(e_{ik}\right)}$$

$$e_{ij} = a(s_{i-1}, h_j)$$



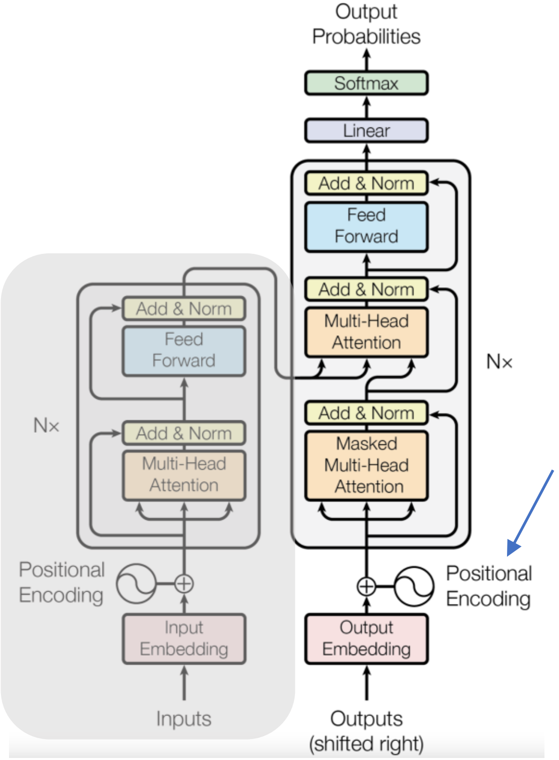
source

multi-headed self-attention:



source

transformer:



source

needed due to permutation invariance of attention

time series: masked self-attention (only attending to past) → decoder-only (auto-regressive)

Demand Forecasting Subtleties

Censored Target

using sales data from past as target quantity to reflect unobservable demand

BUT: sales data correspond to censored demand due to

- out-of-stock situations
- markdown sales: reduced prices for items, e.g., nearing its best before date → increased sales compared to demand at usual, unreduced price

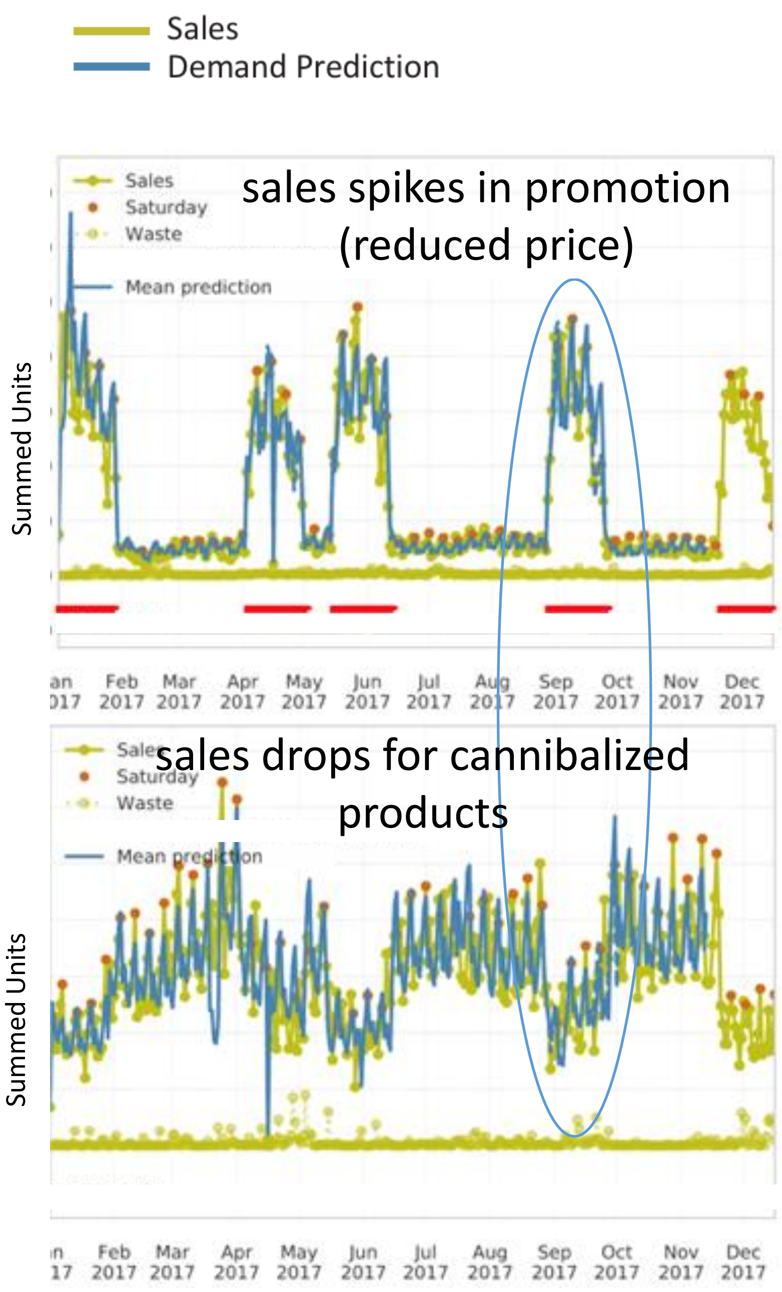
➢ need for (probabilistic) target correction in these situations to enable unbiased demand forecasts

Cannibalization and Halo Effects

sample interactions: demand decreases (cannibalization) or increases (halo) due to other products in promotion at the same time

➢additional ML model(s) after demand forecasting

- prediction residuals as target (all other effects captured)
- learn individual effect for each product pair (product matrix with separate models for each row)
  - price reduction (or promotion flag) of different other products as features
  - feature selection to avoid overfitting (e.g., lasso)



Order Optimization:
Need for PDF Predictions

Replenishment

1. **demand forecasts in form of full, individual probability density functions (PDF)**
2. **order proposals by individually choosing quantile of PDF minimizing expected costs (scaled losses)**

simplistic: **order quantity = current inventory - upcoming demand**
(ignoring delivery lead times and shrinkage beyond demand, e.g., waste)

potential add-on:
(probabilistic) inventory estimation

assumption for two-step approach:
demand (not sales) not affected by subsequent action of ordering

In fact, stock level can have small effects on demand. For example, full shelves might increase demand.

Need for Probability Distributions instead of mere Point Estimators

one best (usually different) quantile for each cost (or loss) function

deviation between
predicted value and truth

examples for losses and their optimal point estimators:

- quadratic loss function (**MSE**) optimized by **mean**
- absolute deviation (**MAD**) optimized by **median**

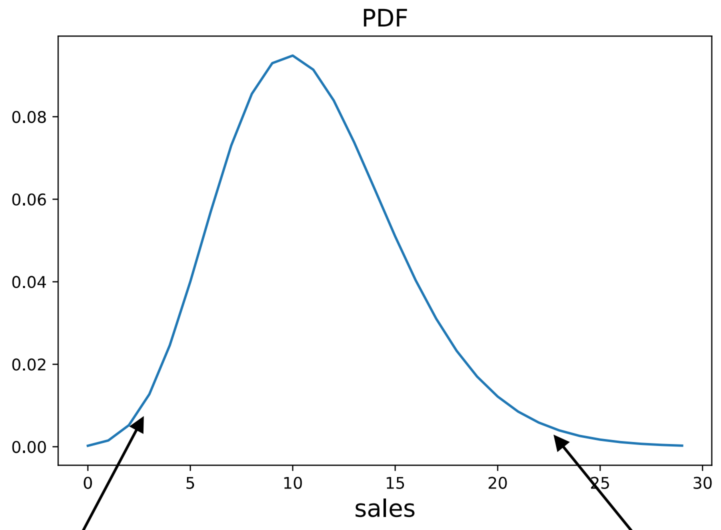
in general: (numerically) find best **quantile** for **arbitrary loss** function by minimizing expected loss

NB: each product (and possibly even different dates for the same product)
can have its **individual cost function** and in turn **individual optimal quantile as point estimator**.

→ **only practical solution: predict full, individual PDFs**

Order Optimization

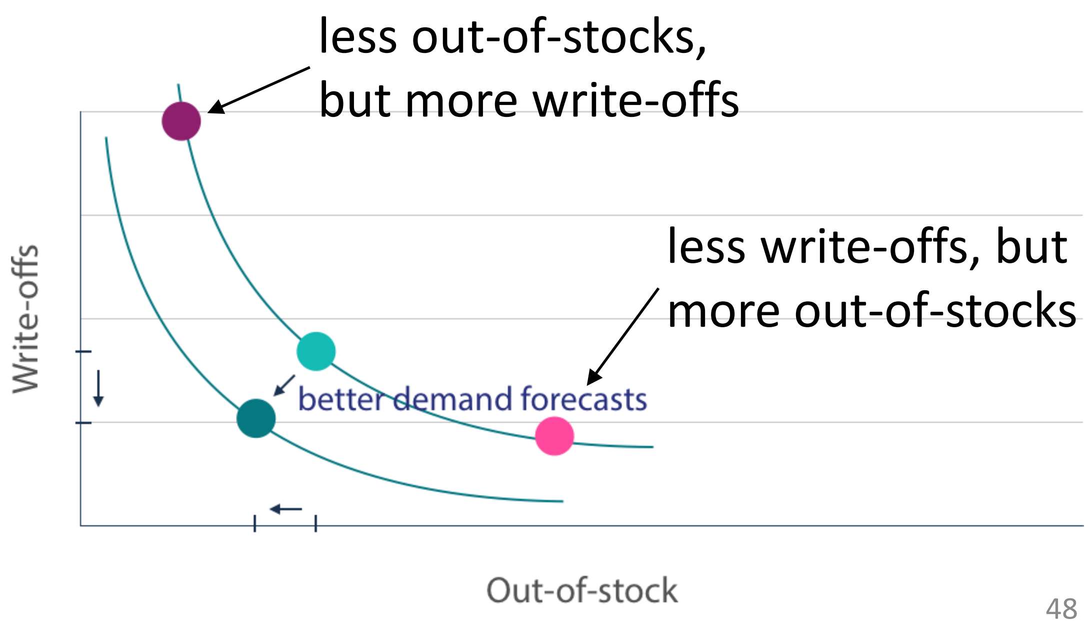
costs refer to **scaled demand losses**: assign costs to out-of-stocks (lost sales), write-offs (waste), ...
→ full **multi-dimensional cost function** as sum of different costs



choose low quantile for ordering: high understock risk

choose high quantile for ordering: high overstock risk

complete cost functions often not available in practice
→ simulate impact of quantile choice on different KPIs (by means of full PDF predictions)



Prediction of Full Probability Distributions

quantile regression:

estimate quantile τ of distribution instead of conditional mean by minimizing

$$(1-\tau)\sum_{y_i<\hat{q}}(y_i-\hat{q})+\tau\sum_{y_i\geq\hat{q}}(y_i-\hat{q})$$

instead of squared error loss

possible with various ML methods, including neural networks and tree-based methods (like random forests or gradient boosting)

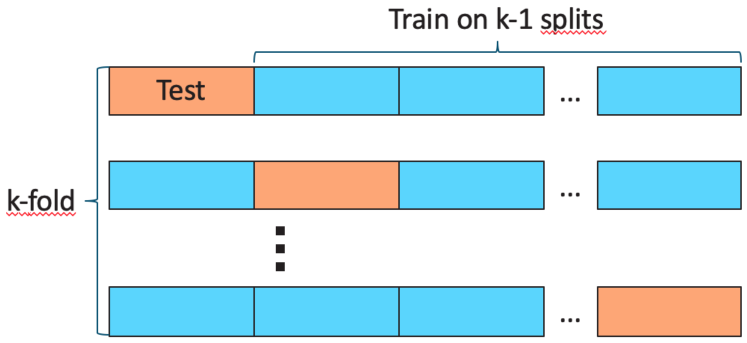
PDF assumption and estimation of moments:

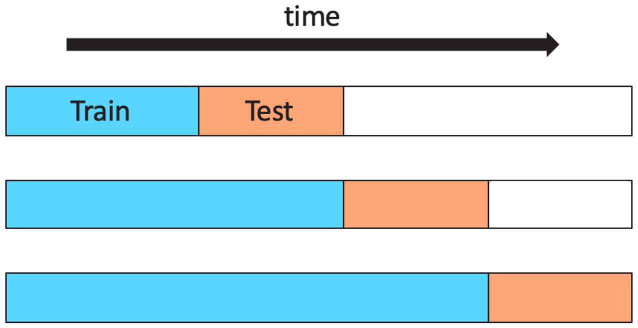
assume, e.g., Gaussian or negative binomial → estimate mean and variance with ML models

Model Evaluation

test structure

cross-validation:





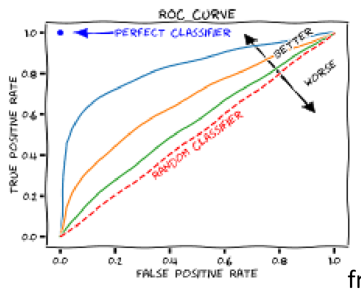
decide on acceptance of model changes by accuracy measure: improved model vs baseline (current best)

measure accuracy of predictions

regression

- point estimate: absolute (MAD, MSE, …) or relative (MAPE, …) metrics
- full probability distribution: a bit tricky

classification

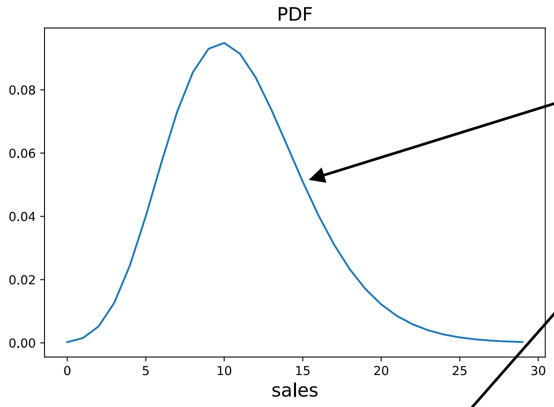


from wikipedia

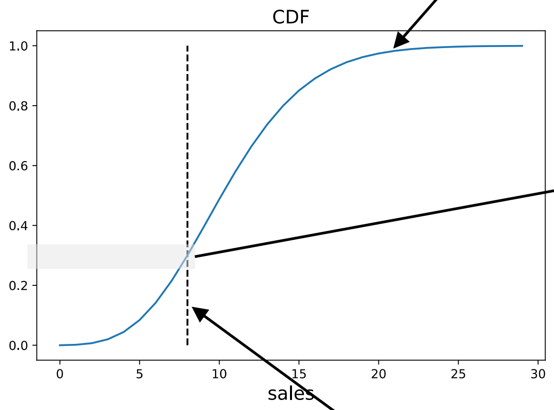
https://arxiv.org/abs/2009.07052

Evaluation of PDF Predictions: Histogram of CDF Observations

individual prediction/observation:



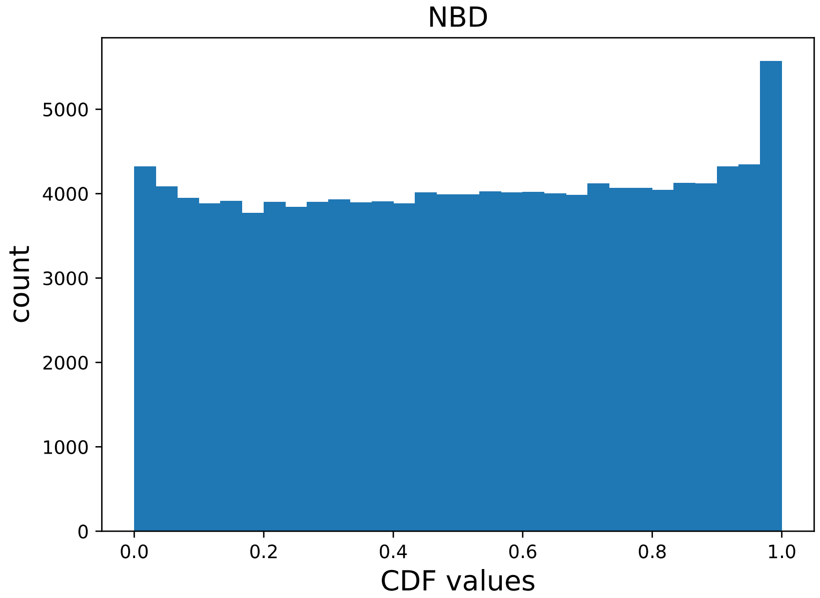
predicted PDF
→ predicted CDF



for each sample

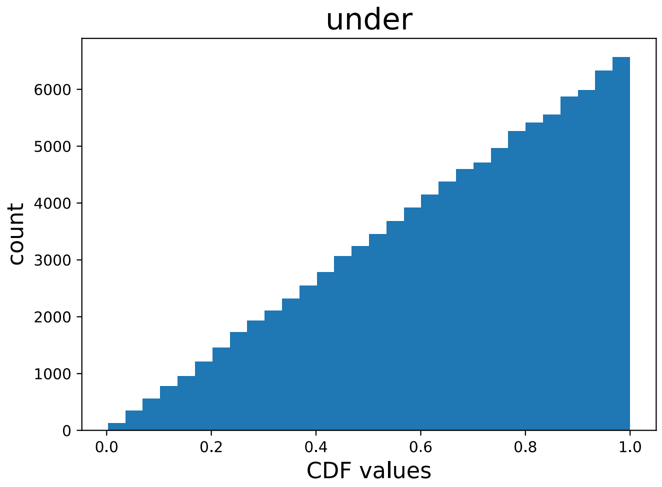
observation (target)

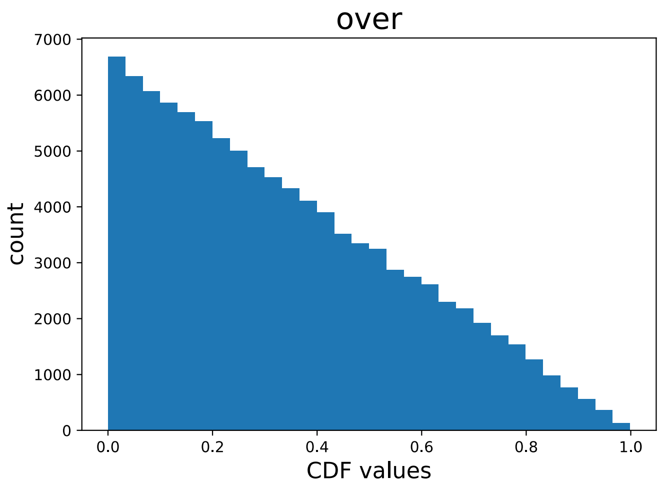
many (or all) predictions/observations:



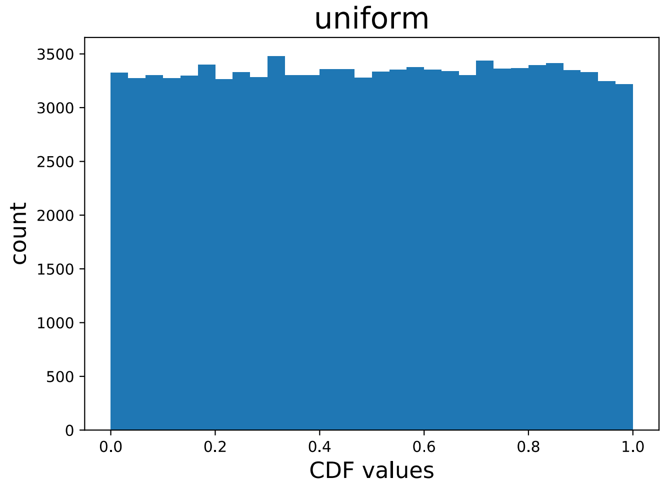
subtlety for discrete PDFs:
histogram filled using random numbers according to the CDF intervals (e.g., for 3 actual sales: random pick between discrete CDF values for 2 and 3)

Interpretation of CDF Histogram

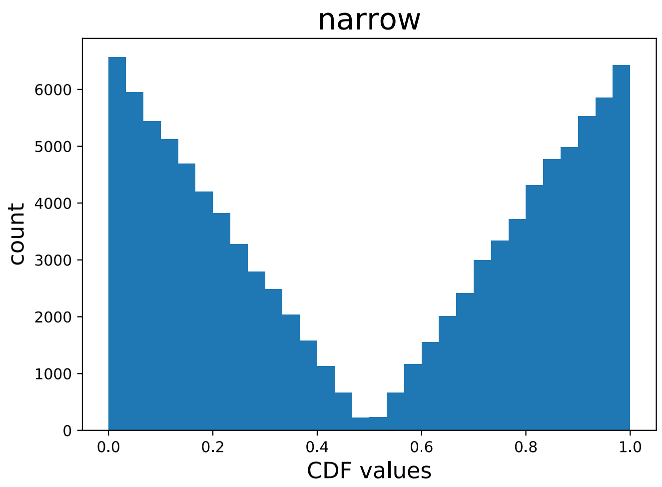


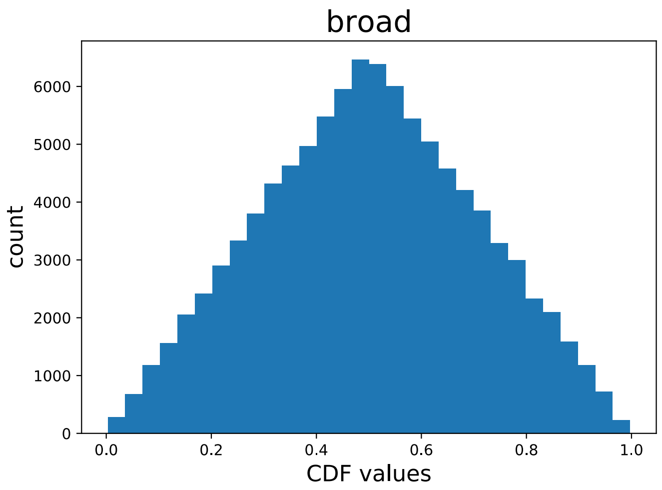


if all is fine ...



quantitative evaluation: measure deviation from uniform distribution (e.g., earth mover's distance)





Demand Shaping: ML and Causality

Data-Generating Process

story behind the data as important as the data itself

Why are the statistical dependencies as observed?

→ data-generating process mostly governed by causal dependencies

but language of algebra symmetric

no way to tell that a storm causes barometer to go down and not the other way around → need for asymmetric mathematical language

The Ladder of Causation

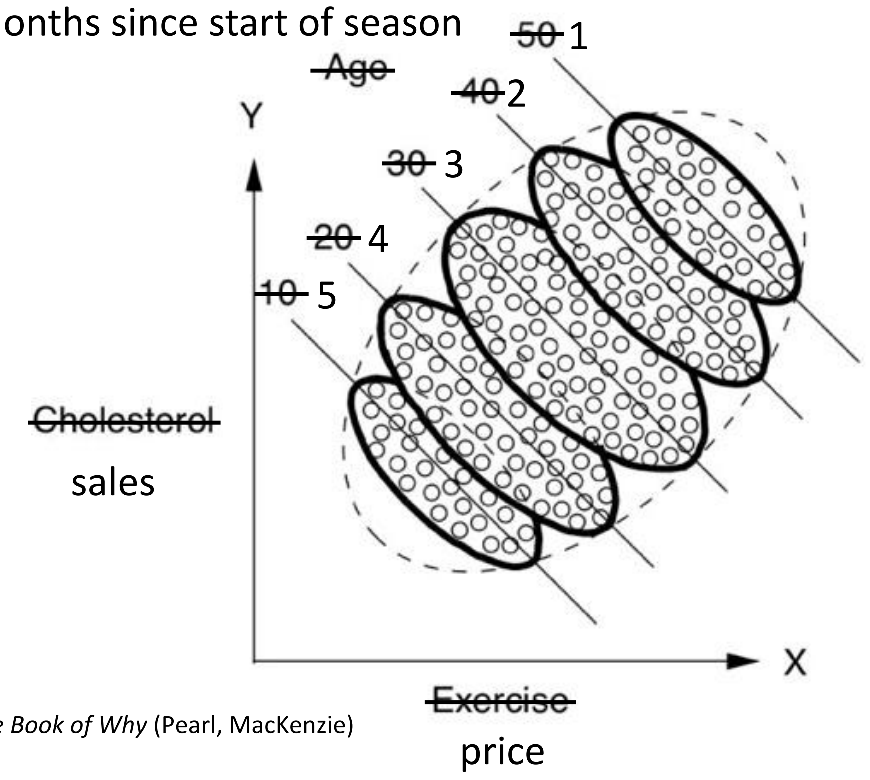
III	*imagining*	**counterfactuals**	What if I had done ...? Why?
II	*doing*	**intervention**	What if I do ...? How?
I	*seeing*	**association**	What if I see ...? → Realm of ML

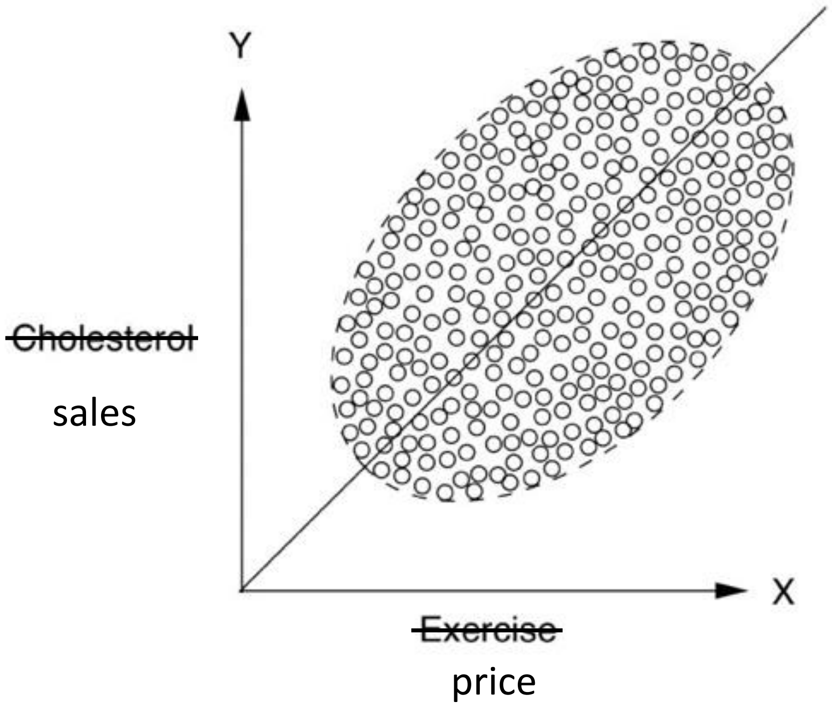
from *The Book of Why* (Pearl, MacKenzie)

Simpson’s Paradox

example: monthly sales of a fashion article in different shops during winter season

Lower price yields higher sales for each month individually, but lower sales overall?



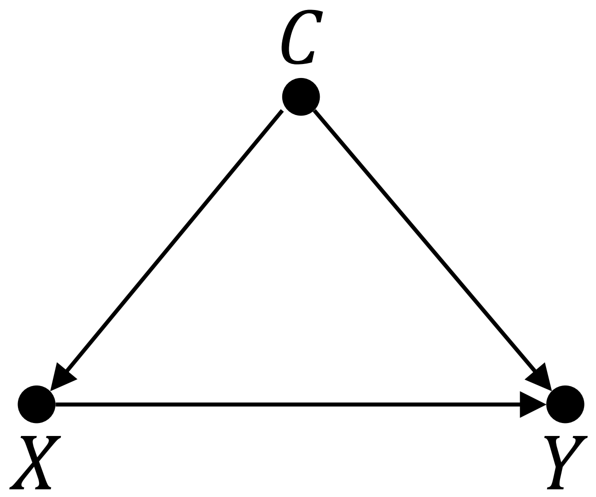


from *The Book of Why* (Pearl, MacKenzie)

Confounding

causal effect of X on Y confounded by common cause C:

$$X \leftarrow C \rightarrow Y$$



→ spurious correlation between X and Y

(overlaying potential true causal effect of X on Y)

common cause principle:

every correlation either due to a direct causal effect linking the correlated entities or brought about by a third factor (confounder)

Confounders for Pricing

price setting for a product can be considered a demand shaping method

the idea is a causal effect: lower price leads to higher demand

→ by estimating this causal effect one can find an optimal price according to a given policy (like maximizing profit)

problem: confounders influencing both pricing in past (obverved) data and demand, e.g., lowering prices on weekends only for grocery or lowering prices toward end of a season for fashion (most sales at beginning of season)

Counterfactuals

fundamental problem of causal inference:
only one realization: *What happened? And what could have happened instead?*
→ cannot observe different **potential outcomes (individual causal effect)**

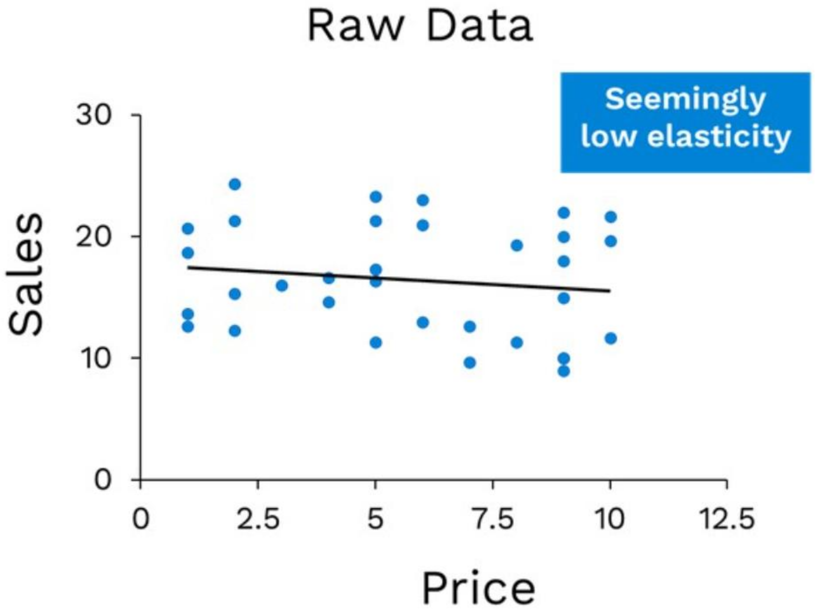
example for application of **causal what-if scenario**:
individual (e.g., per product-location-date combination) demand shaping via price setting

ML and data not enough to describe causal structure
→ need for **causal assumptions** as add-on to ML (going beyond curve fitting)

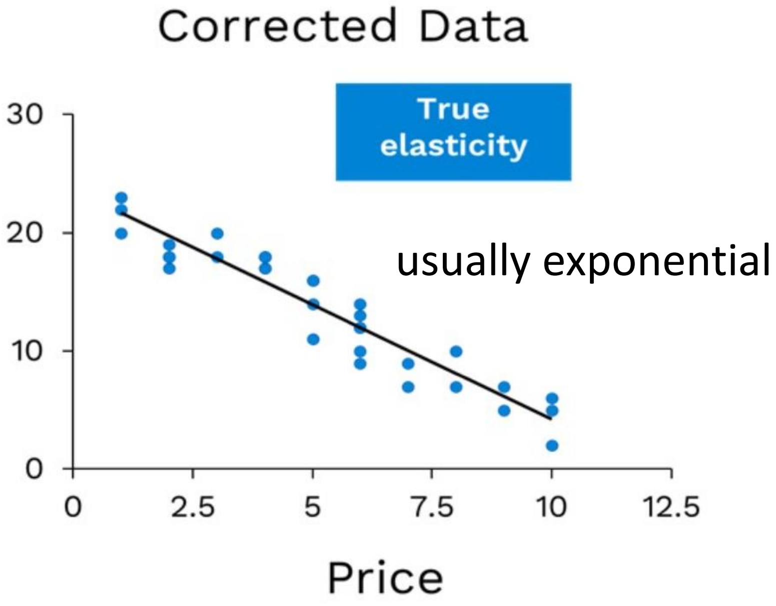
Demand Shaping with Causal Inference

dynamic pricing: influencing demand of different products by price setting

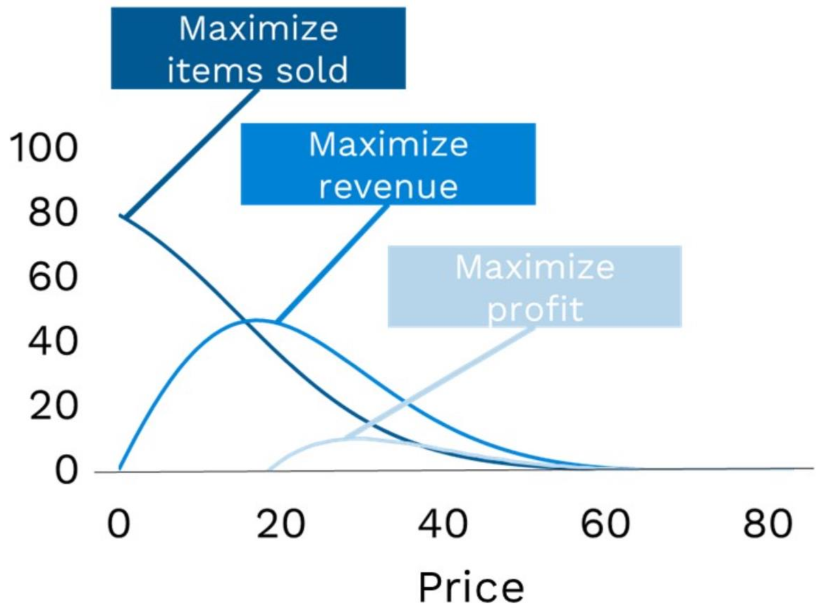
confounded effect:



after de-confounding:



use for pricing policies:



customer targeting: influence individual customer demand by sending coupons

Potential Outcomes with ML

deconfounding

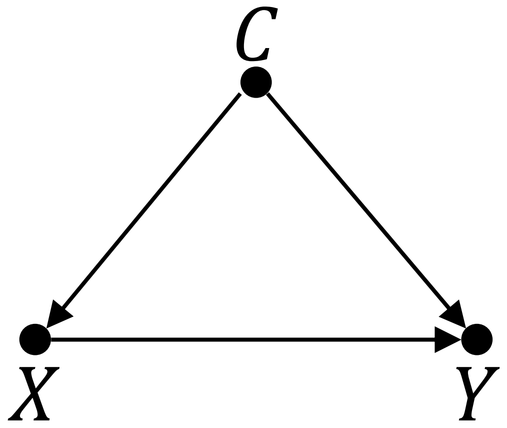
by RCTs or

independence weights (inverse propensity scores)

prediction of individual causal effect with ML model

(generalization by function approximation)

Independence Weights with ML



scenario: X binary (for simplicity), several confounders C

aim: prediction of individual causal effect using observational data only

i. ML model to predict past action policy $P(X|C)$ (beware: need to include all C)
ii. inverse propensity score weighting of each unit (to adjust for multiple confounders):

$$P(Y|do(X)) = \sum_z P(Y|X, Z = z)\, P(Z = z) = \sum_z \frac{P(Y, X, Z = z)}{P(X|Z = z)}$$

alternative: A/B test

iii. train ML model on deconfounded data to predict Y with X and C as features
iv. individual causal effect as difference between predictions for setting feature $x = 1$ and $x = 0$, respectively (what-if scenario)