Advanced Topics in Machine Learning

Winter Semester 2024/2025

Prof. Dr.-Ing. Christian Bergler | OTH Amberg-Weiden

Overview

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Topics of Today: Advanced Deep Learning Strategies – Part III

- Self-Supervised Learning
- Active Learning

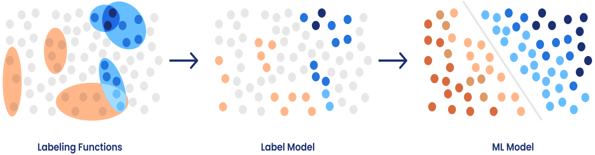
Topics of Today: Advanced Deep Learning Strategies – Part III

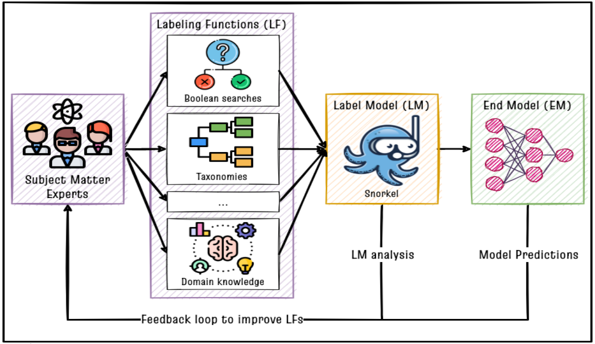
- Weak Supervision
- N-Shot Learning
- Causal Learning

Deep Learning Strategies – Part III

Weak Supervision

- Goal: How to transfer an unsupervised to a (weakly) supervised task!





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Deep Learning Strategies – Part III

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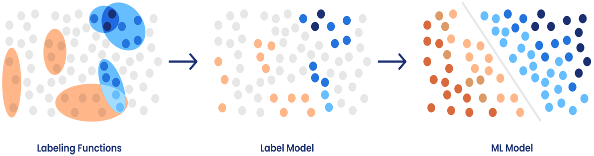
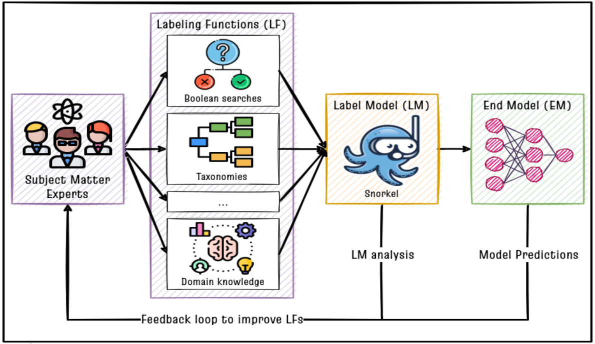
- Goal: How to transfer an unsupervised to a (weakly) supervised task!
- Interpret & categorize high-level, scalable, and potentially noisy signal sources by applying multiple sources of supervision





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Weak Supervision

- Goal: How to transfer an unsupervised to a (weakly) supervised task!
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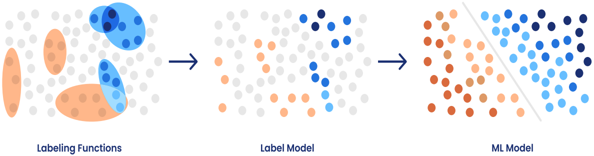
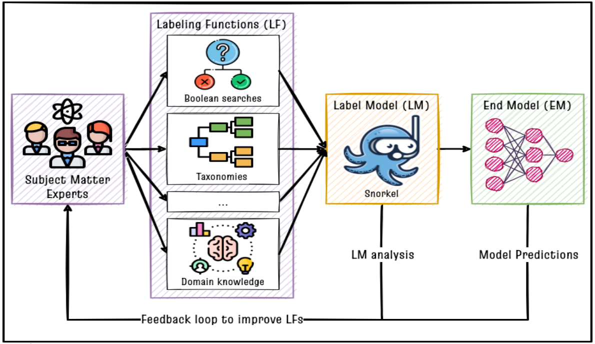
- Create large training sets, based on unlabeled data, much more quickly than using a 1-by-1 manual supervision





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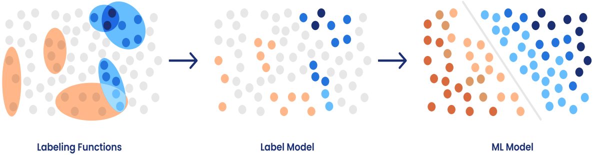

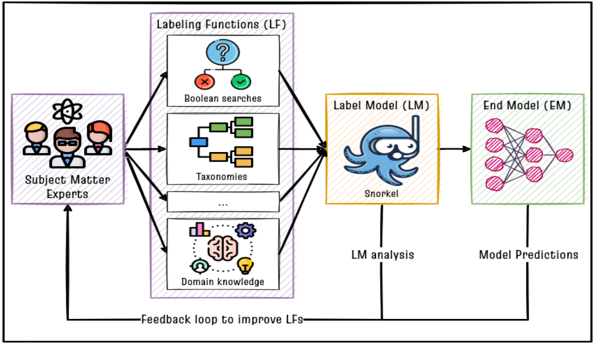

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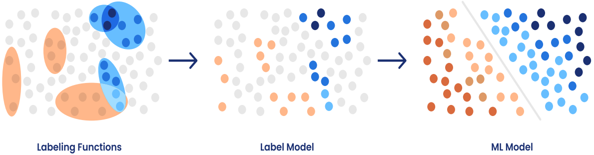
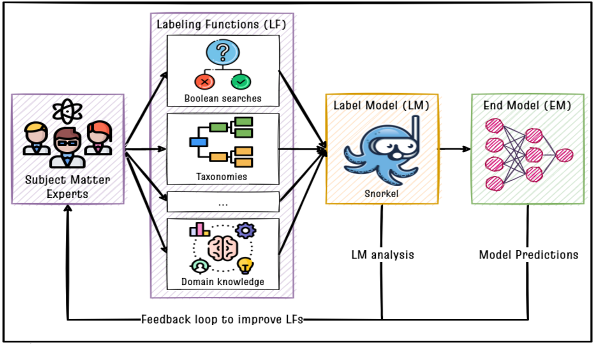
- Lack of precision: completely labeled, but often not precisely enough to recognize subtle differences





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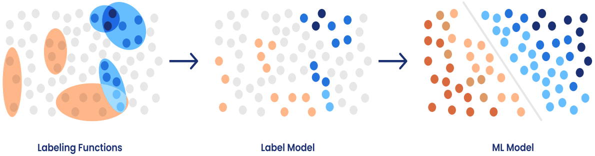

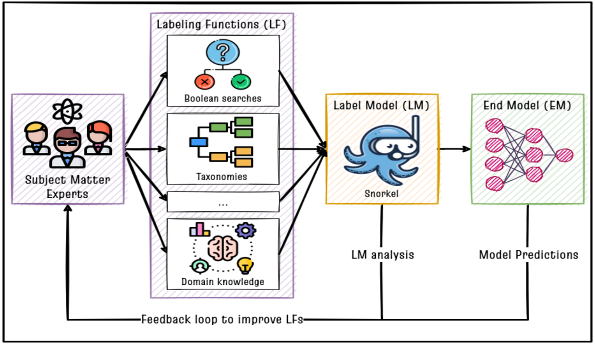

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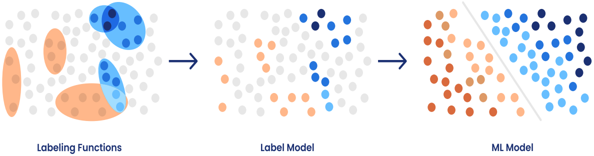

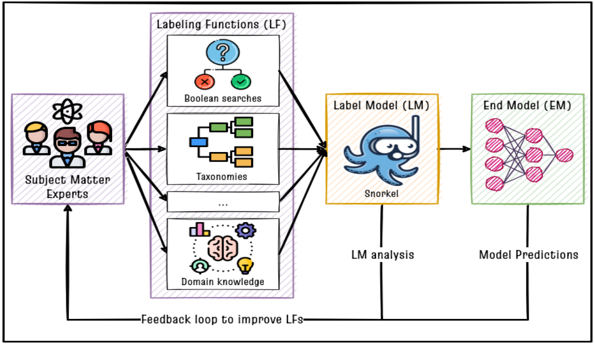

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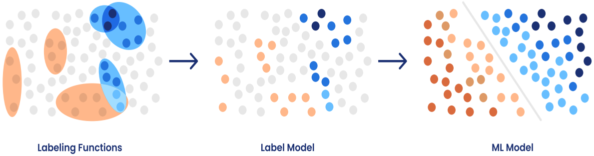

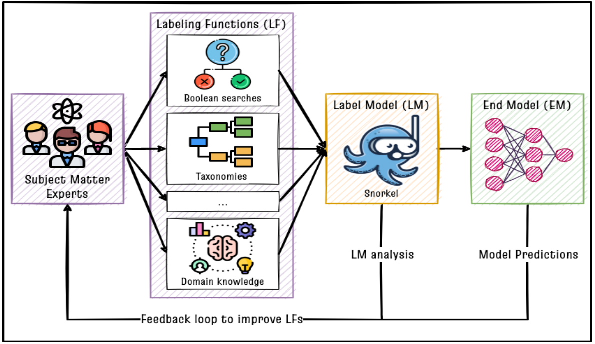

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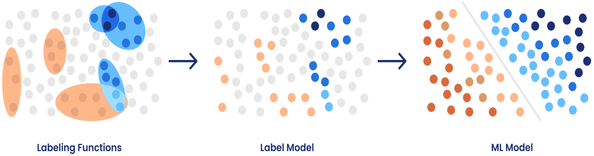
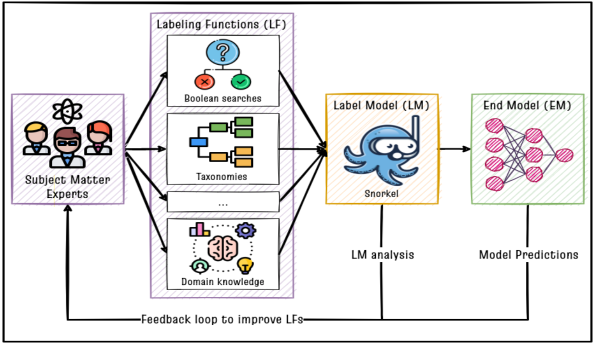
- Idea: trade-off 100,000 pretty good vs. 100 perfect data labels





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prob of diversity of 100 perfect is less than prob diversity of 100000 get rid of false classification: de noise

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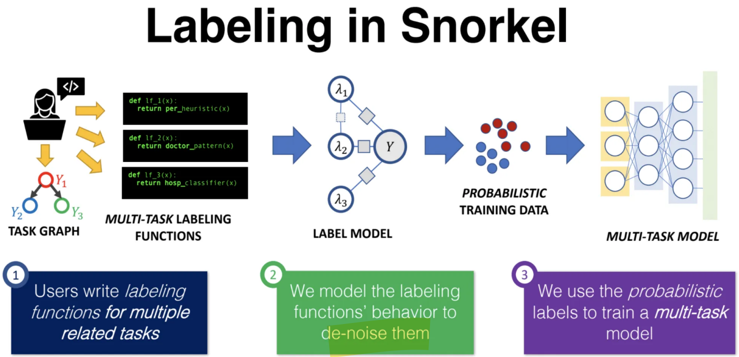
Snorkel Framework



- Labeling functions λ_N (simple functions/rules), providing multiple inconsistent or overlapping labels (commercialized version available here: Snorkel)
- Combine noisy weak labels in a labeling model to generate a consensusmore accurate final label
- Label model learns dependencies/reliabilities of the labeling functions, weighting each function according to its accuracy and overlap with others
- Probabilistic labels for each sample, allow to build a (weakly) supervised training set

Source: Link to Image

Smart Labeling

- Labeling involves using automated or semi-automated techniques to label data intelligently (see pseudo-labeling, self-supervised approaches)

Source: Image from OTH-AW, Electrical Engineering, Media and Computer Science, Thomas Nierhoff – Vorlesung Advanced Topics in ML

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- Active Learning: label only the most uncertain or informative data points, making the labeling process more efficient

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Deep Learning Strategies – Part III

Weak Supervision

Application: Cut-In Prediction Autonomous Vehicle

- Refers to predicting when another vehicle in adjacent lanes will “cut in” or merge into the lane occupied by the autonomous vehicle (critical for safe driving!)

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every potential event has to be taken into account

here patrren recognition is important

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- Unlabeled data: process large amounts of unlabeled driving data with weakly supervised trained models that learn to identify "cut-in" scenarios indirectly

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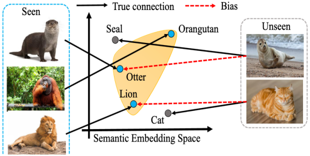
train model on weakly supervissed data sets. from sensor data, heuristics etc and unlabeled

Deep Learning Strategies – Part III
N-Shot Learning

N-Shot Learning – Zero-Shot, Single-Shot & Few-Shot Learning

Idea: Zero-shot, single/one-shot, and few-shot learning are learning paradigms where models identify/categorize or generate new categories with very few or even no labeled examples

- Zero-Shot Learning: identify new categories never seen in training by leveraging auxiliary semantic knowledge based on feature similarity via textual/visual embeddings!



(a) a tapir made of accordion. a tapir with the texture of an accordion. (b) an illustration of a baby hedgehog in a christmas sweater walking a dog

Source: https://medium.com/@vireshj/zero-shot-learning-understanding-machines-that-learn-like-humans-e670f83186b8
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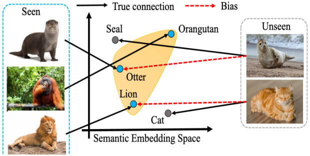

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zero shot for first time seeing few shot is for few times seeing

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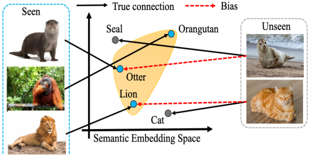
- Non-static set of classes, while unseen events will be stored in the high-dimensional feature space either near (related to "Knowns") or far-apart (unrelated to "Knowns")
- Class assignment for a first-time appearance of a new category requires pre-existing knowledge (embeddings, e.g. single-shot) describing the new class



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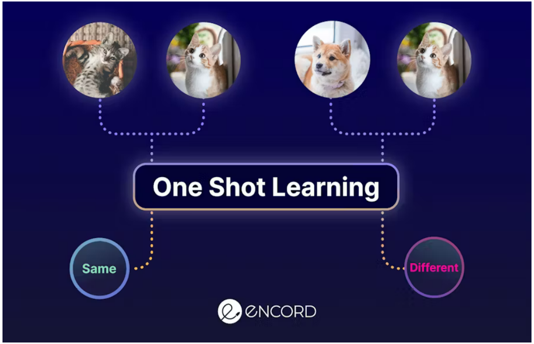

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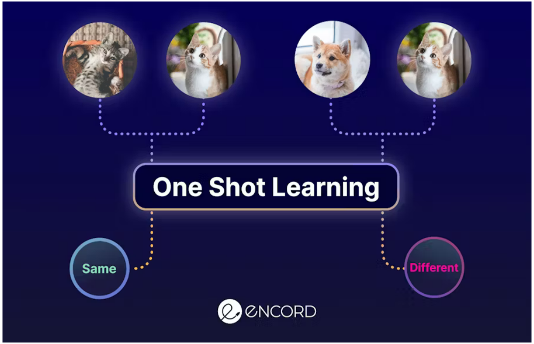

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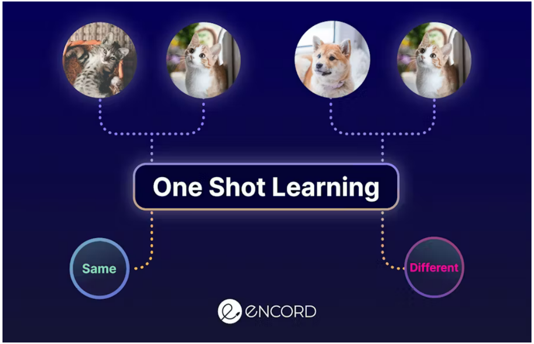

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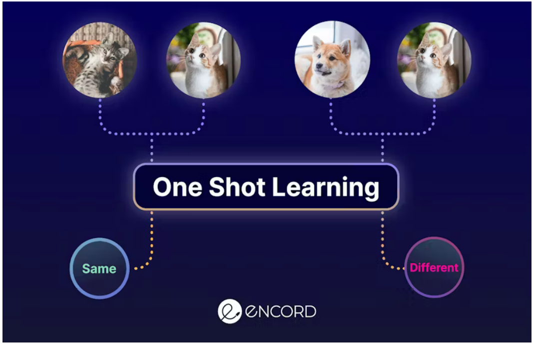
- Class assignment is based on distance-related outcome ("close enough") of an unseen sample w.r.t. the "single shot data point"



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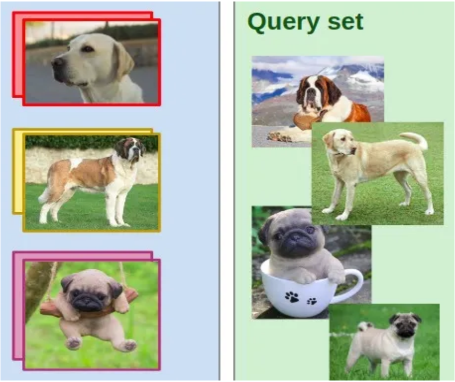

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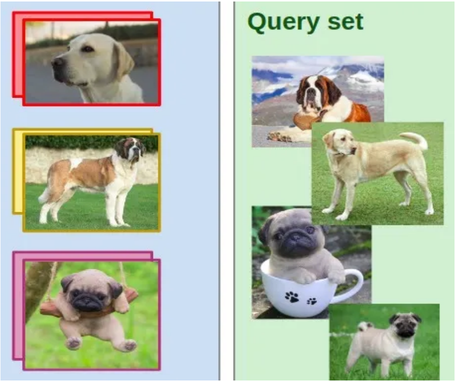

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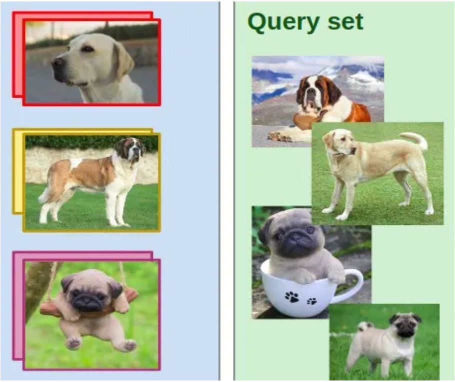
- Often a K-way N-Shot classification problem, with K as the number of classes and N as the class-specific small number of labels, together with Q many query images



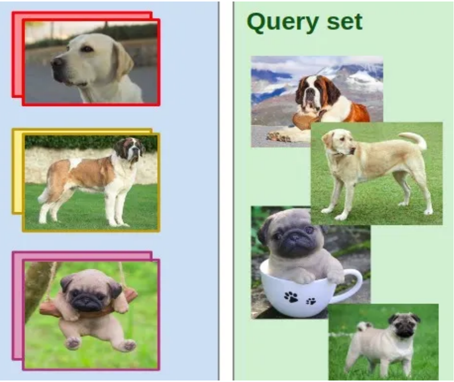
Source: https://neptune.ai/blog/understanding-few-shot-learning-in-computer-vision

Deep Learning Strategies – Part III

N-Shot Learning

causal learning home work

- Few-Shot Learning: model learns from a small number of labeled examples, with more than zero/one images to compare against
- Number of labeled "shots" $N < 10$, usually between 2 to 5, while model generalization is based on this small set of instances
- Often a K-way N-Shot classification problem, with K as the number of classes and N as the class-specific small number of labels, together with Q many query images
- Classify Q query images among the K classes, with $K \times N$ samples in the training set are the only representatives



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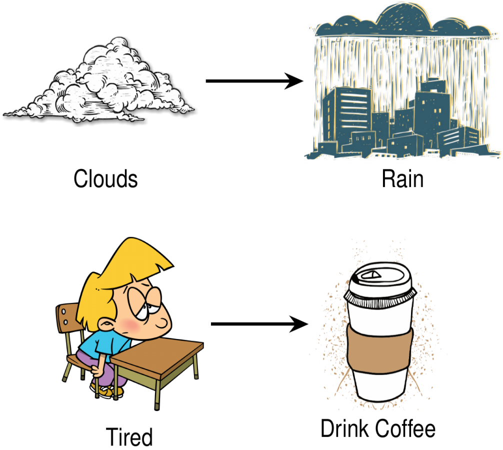
Deep Learning Strategies – Part III

Causal Learning

- Implies a direct cause-and-effect relationship ("explain the cause of an effect") between two variables (change one variable will directly impact the other in a predictable way)

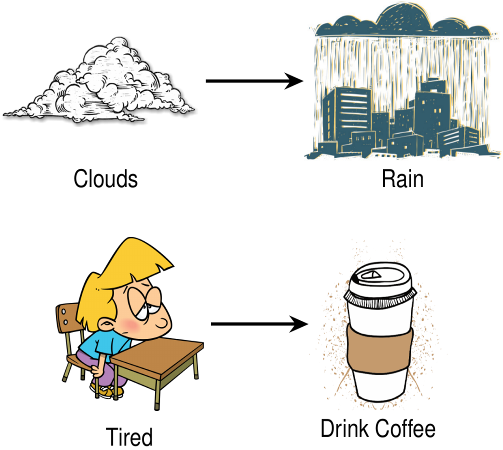


Source: FAU Erlangen-Nuremberg, Pattern Recognition Lab, K.Breininger, V. Christlein, Advanced Deep Learning – Interpretable/Causal Deep Learning

Deep Learning Strategies – Part III

Causal Learning

- Implies a direct cause-and-effect relationship ("explain the cause of an effect") between two variables (change one variable will directly impact the other in a predictable way)
- Careful: correlation describes a statistical association between two variables and indicates a simultaneous change (trend!) $\rightarrow$ However, not necessarily causing the other!



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Deep Learning Strategies – Part III

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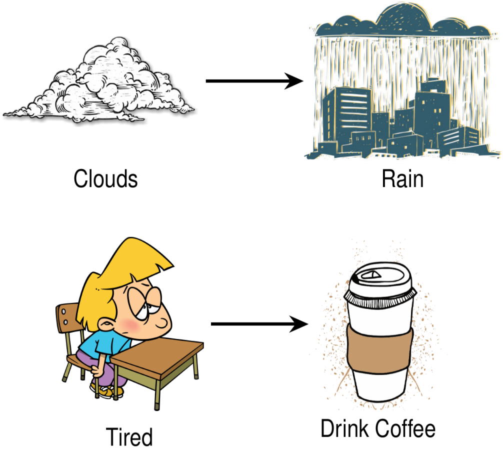
- Careful: correlation describes a statistical association between two variables and indicates a simultaneous change (trend!) $\rightarrow$ However, not necessarily causing the other!
- Causal inference often uses statistical methods to identify relationships that are not simply correlations but have a directional influence



Source: FAU Erlangen-Nuremberg, Pattern Recognition Lab, K.Breininger, V. Christlein, Advanced Deep Learning – Interpretable/Causal Deep Learning

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Types of Causal Relationships

- Direct Causal Relationships: One variable directly affects another (e.g., smoking directly causes an increased risk of lung cancer)
- Indirect Causal Relationships: The effect of one variable on another is mediated through a third variable (e.g., education may lead to higher income, and higher income might then lead to better health outcomes)
- Bidirectional Causality: Some relationships may involve mutual causality, where two variables affect each other (e.g., diet and exercise can both affect each other over time)

Source: FAU Erlangen-Nuremberg, Pattern Recognition Lab, K.Breininger, V. Christlein, Advanced Deep Learning – Interpretable/Causal Deep Learning

Deep Learning Strategies – Part III

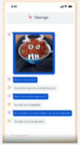
Causal Learning

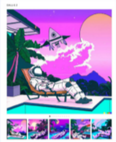
Deep Learning

Representation Learning

Continuous Optimization

Handling Large Quantities of Data

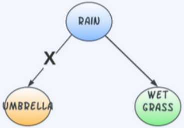




Causality

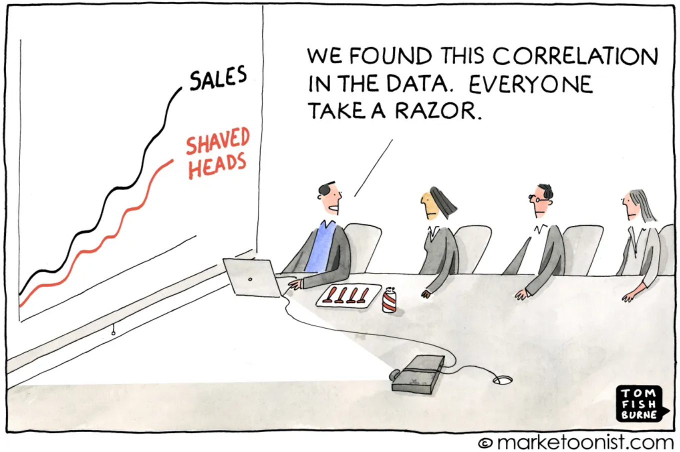
Model Cause and Effect

Answer Interventional Questions



Source: Image from Nan Rosemary Ke, Stefan Bauer, "Causality and Deep Learning: Synergies, Challenges and the Future", Slide 29

Correlation is NOT Causation!

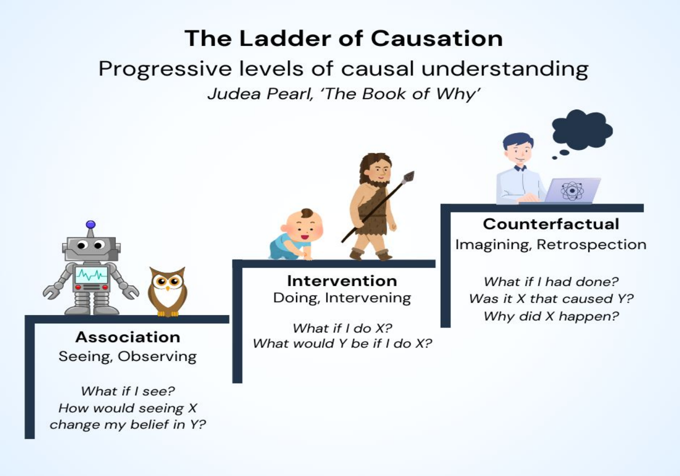


Source: Image from https://censemaking.com/2022/08/03/the-fear-and-folly-of-data/

Deep Learning Strategies – Part III

Causal Learning

Ladder of Causation



- Organizes causal reasons into three hierarchical levels: association, intervention, counterfactuals
- From simply observing data to fully understanding & reasoning about causal mechanisms

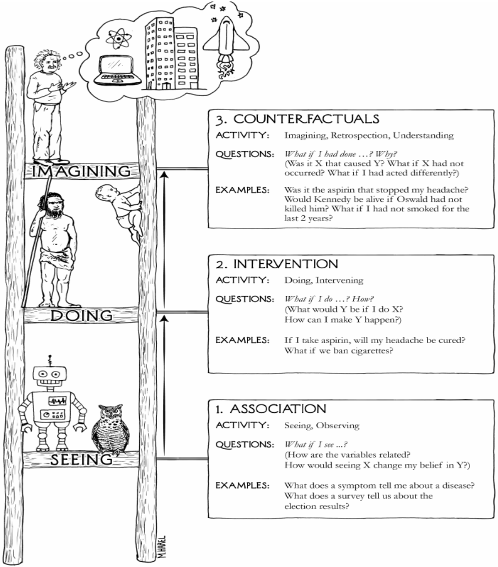
Source: Image from https://www.linkedin.com/posts/causai-bv_ladderofcausation-causalai-decisionmaking-activity-7177992092458057729-hiP9

Deep Learning Strategies – Part III

Causal Learning

Association

- Observing correlations/dependencies of variables: "What happens if we change this variable?"



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Deep Learning Strategies – Part III

Causal Learning

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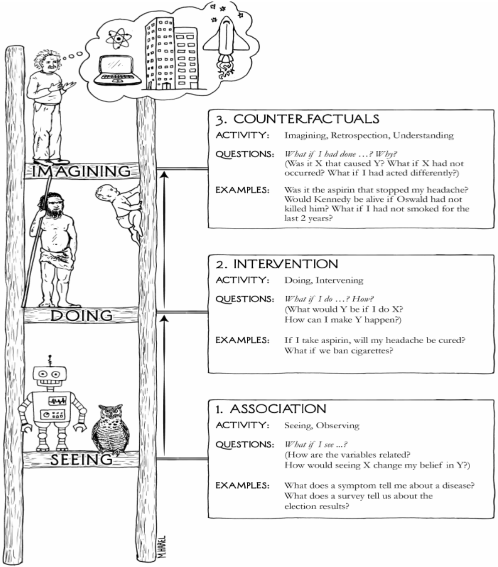
- However, no explanation why one thing happens because of another (purely observational!)



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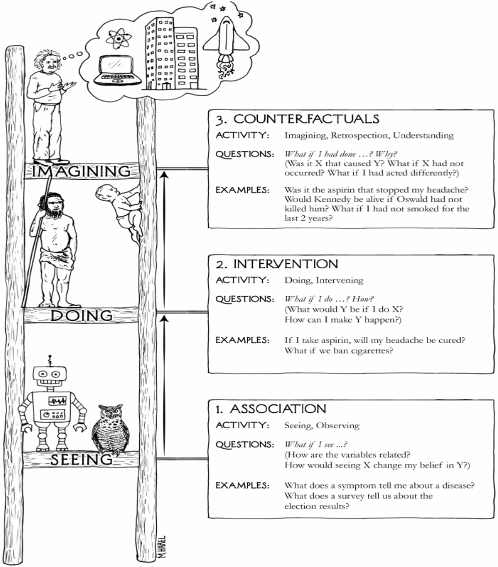

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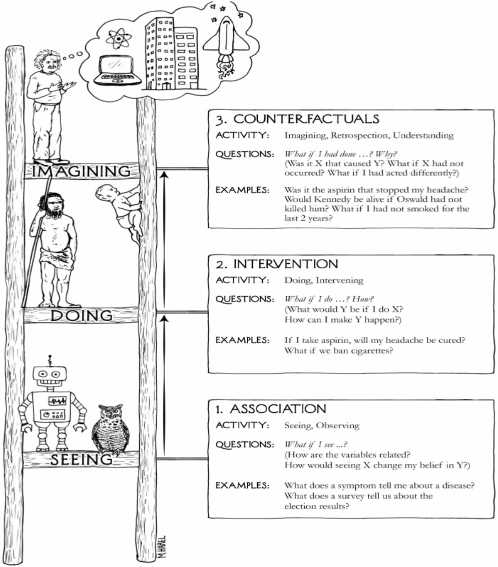

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Deep Learning Strategies – Part III

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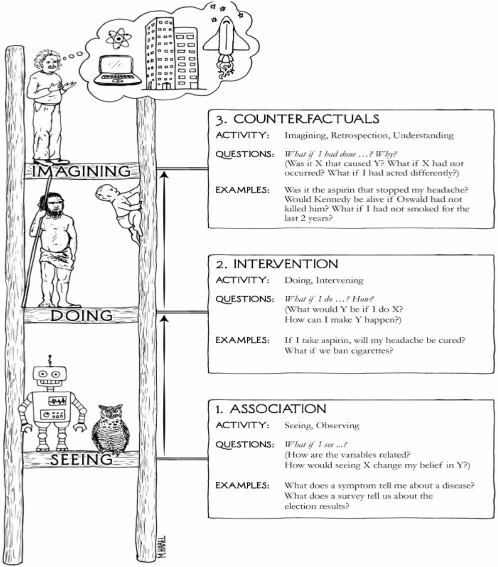
- However, no explanation why one thing happens because of another (purely observational!)
- Questions:“What is the probability of Y given X?
- Methods: traditional statistical methods, ML (linar regression, classification, clustering)
- Association alone do not determine if a relationship is causal (correlation between ice cream sales and drowning incidents does not impl that buying ice cream causes drowning)



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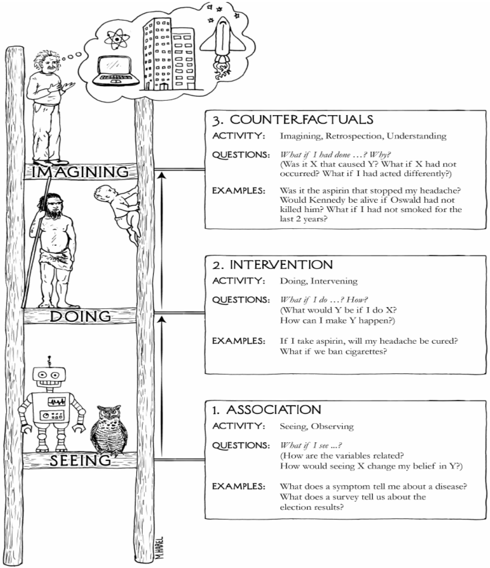
Deep Learning Strategies – Part III

Causal Learning

Intervention

- Moving beyond observation by introducing actions to change the system and observing the results: "What if I do this?"



Source: FAU Erlangen-Nuremberg, Pattern Recognition Lab, K.Breininger, V. Christlein, Advanced Deep Learning – Interpretable/Causal Deep Learning

Deep Learning Strategies – Part III

Causal Learning

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- Moving beyond observation by introducing actions to change the system and observing the results: "What if I do this?"
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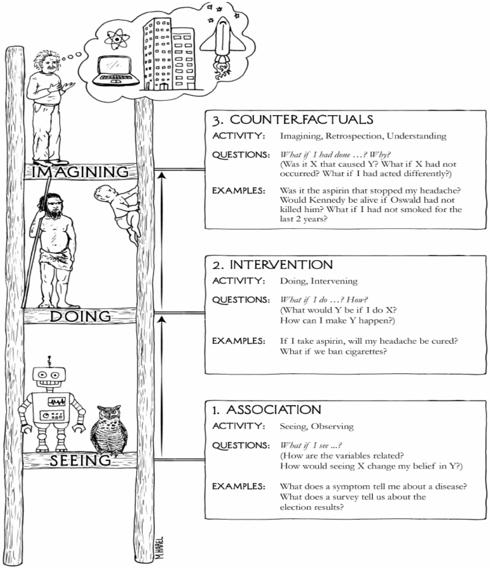

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Deep Learning Strategies – Part III
Causal Learning

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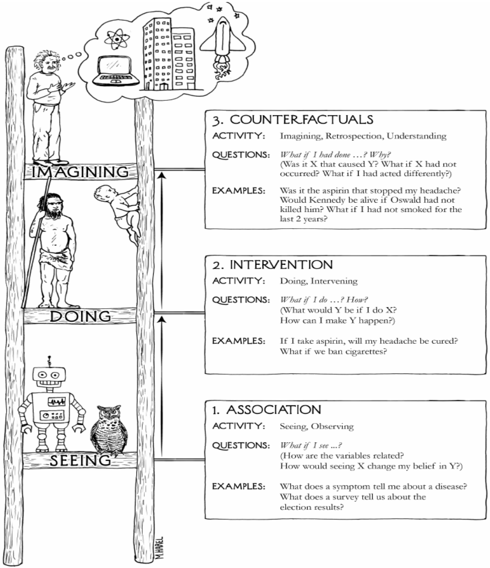

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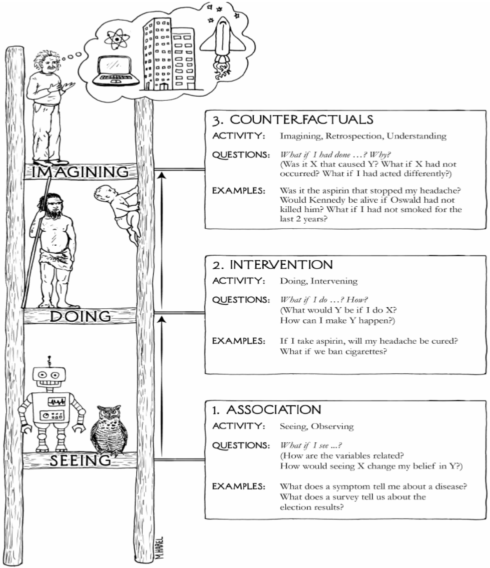
- Moving beyond observation by introducing actions to change the system and observing the results: "What if I do this?"
- Represent causal relationship by showing how changes in one variable affect another
- Question: "What will happen to Y if I change X?"
- Methods: randomized controlled trials, where the experimenter manipulates the independent variable $P(Y|do(X))$ (e.g. giving patients a treatment placebo) to observe the effect on a dependent variable (like recovery rates)



Source: FAU Erlangen-Nuremberg, Pattern Recognition Lab, K.Breininger, V. Christlein, Advanced Deep Learning – Interpretable/Causal Deep Learning

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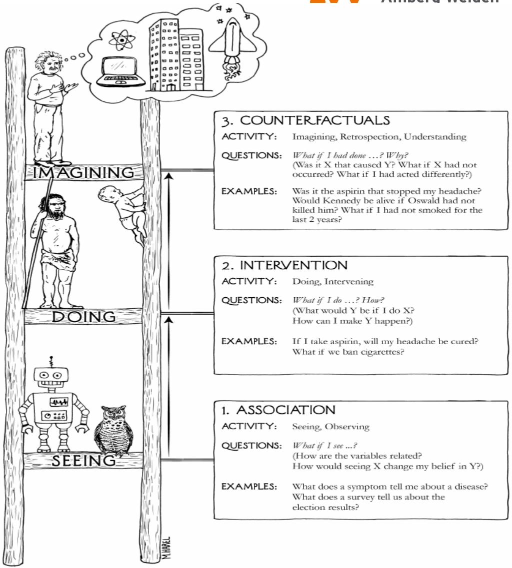
Counterfactuals

- Asking about hypothetical alternatives to what actually happened, what would have happened “if”



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Deep Learning Strategies – Part III

Causal Learning

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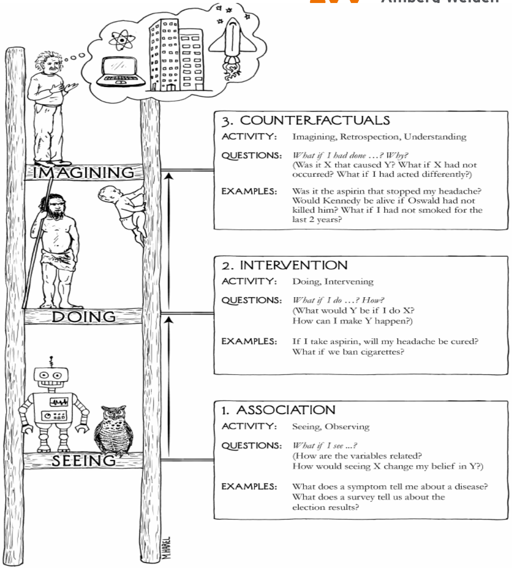
- Asking about hypothetical alternatives to what actually happened, what would have happened "if"
- Alternative realities by imagining what the outcome would have been if a different action or condition had been in place



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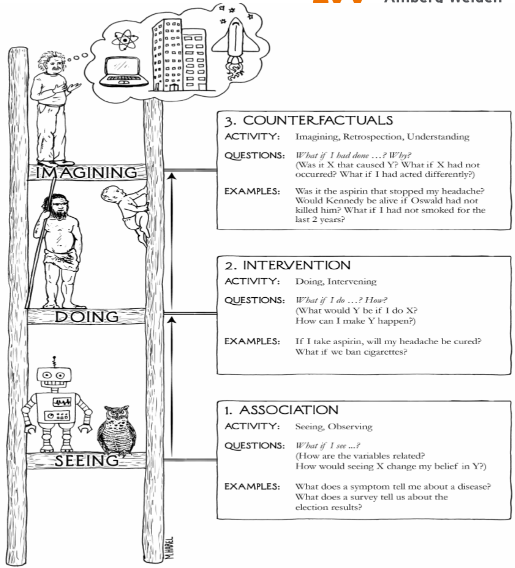

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Deep Learning Strategies – Part III

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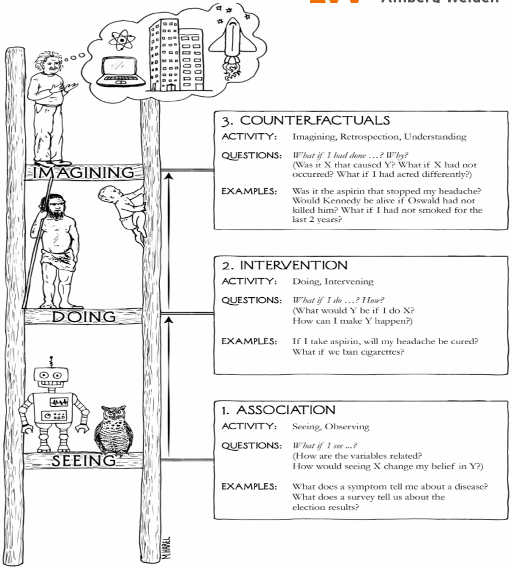
- Methods: structural causal models (SCMs), provide a framework for understanding causal relationships at a deeper level by specifying equations reflecting mechanisms of causation



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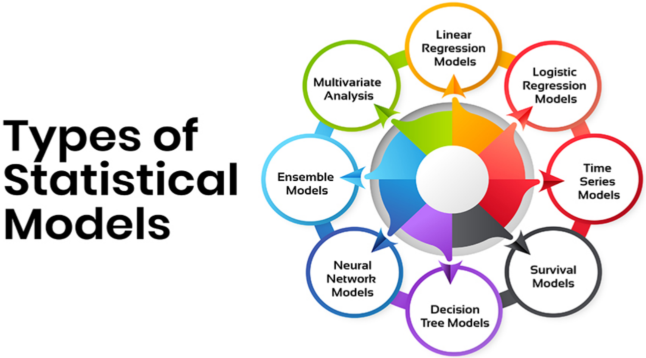

- Current ML-Models or statistical models can only do "Association"

Source: https://www.dasca.org/world-of-data-science/article/what-is-statistical-modeling-in-data-science

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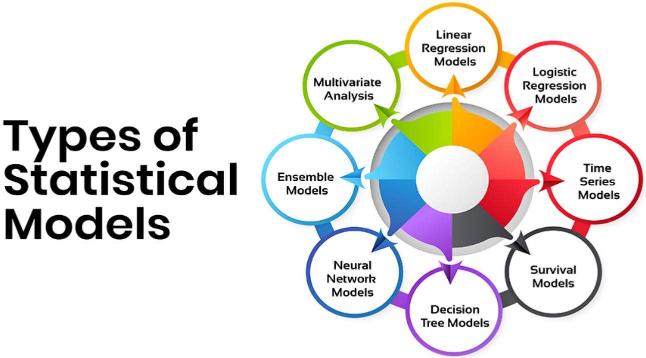
Causal Learning



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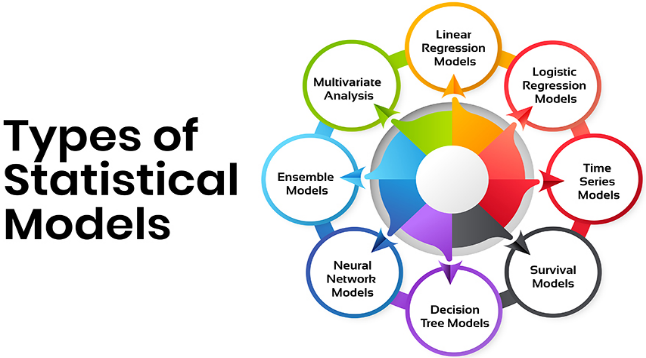

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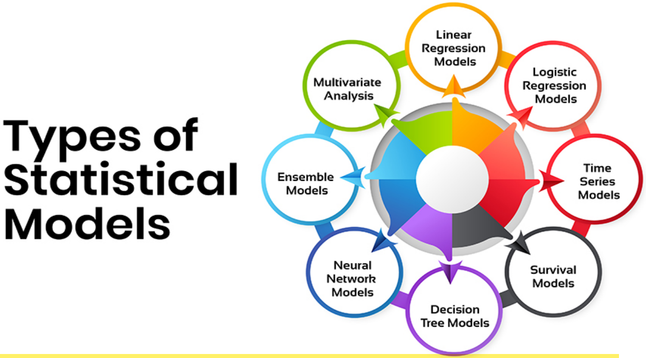
Deep Learning Strategies – Part III

Causal Learning



here we have assosiations only becasue of current ml modles

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- Statistical inference → $P(Fire|Smoke)$, $P(Smoke|Fire)$ obsevation p(s/m); is more
- No Causal Inference → Yes: Fire causes Smoke, No: Smoke causes Fire reality
- Successful because: massive amount of data, high number of parameters, strong computational power, independent and identically distributed (i.i.d.) assumption

data samples dont effect each other

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Deep Learning Strategies – Part III

Causal Learning

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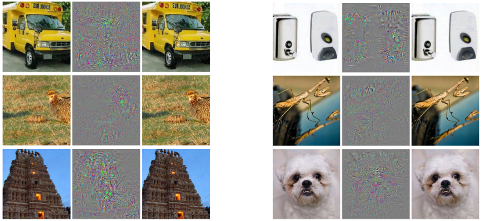

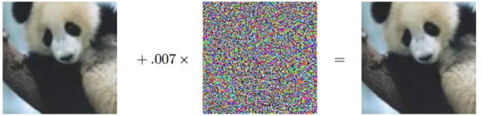

Source: Szegedy et al., Intriguing properties of neural networks, Figure 5

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Deep Learning Strategies – Part III

Causal Learning

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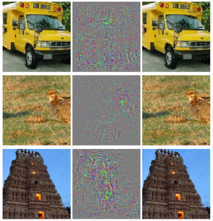

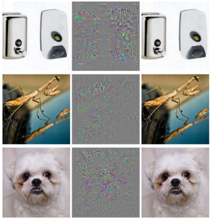

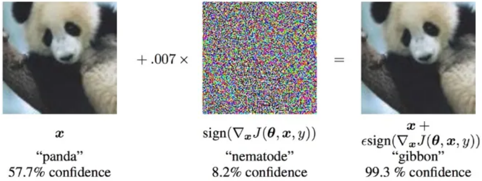

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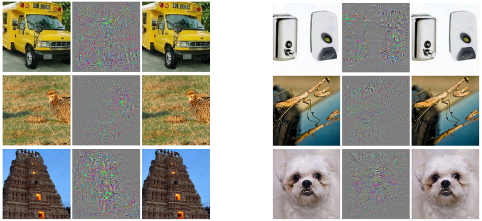

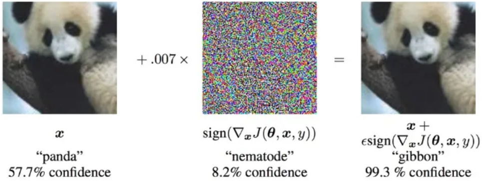

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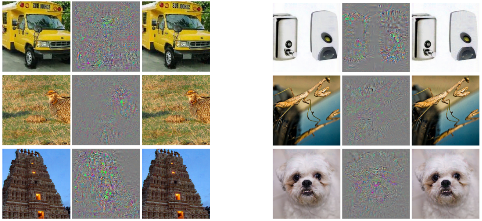
- Introducing an unexpected distribution change?



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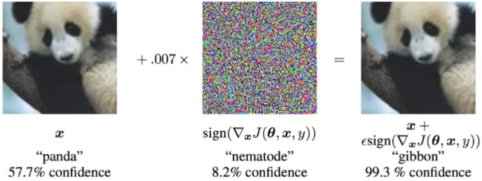

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Common Causal Principles

- Causal Learning will help ML-models to plan and act according to interventions

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- Robust to distribution shifts, using counterfactual questions to learn unseen data
- Help towards important goals of ML: Generalization, Transfer Learning, Explainability
- Explains the connection between causality and statistical dependence
- Postulated by Hans Reichenbach in 1956: given two observations X and Y are statistically dependent $\rightarrow P(X, Y) \neq P(X)P(Y)$, then an event Z which causally influences both results in $P(X, Y|Z) = P(X|Z)P(Y|Z)$

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- Robust to distribution shifts, using counterfactual questions to learn unseen data
- Help towards important goals of ML: Generalization, Transfer Learning, Explainability
- Explains the connection between causality and statistical dependence
- Postulated by Hans Reichenbach in 1956: given two observations X and Y are statistically dependent $\rightarrow P(X, Y) \neq P(X)P(Y)$, then an event Z which causally influences both results in $P(X, Y|Z) = P(X|Z)P(Y|Z)$
- If Z is not observed (hidden), it is a confounding variable, affecting both the cause and the effect, making it difficult to establish a true causal relationship

Source: FAU Erlangen-Nuremberg, Pattern Recognition Lab, K.Breininger, V. Christlein, Advanced Deep Learning – Interpretable/Causal Deep Learning

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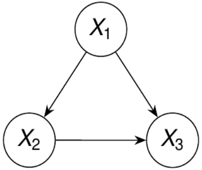
- Example: exercise frequency (Z), body weight (X), cholesterol levels (Y) $\rightarrow$ without considering Z, it might appear that body weight directly affects cholesterol, however, exercise impacts both independently

Source: FAU Erlangen-Nuremberg, Pattern Recognition Lab, K.Breininger, V. Christlein, Advanced Deep Learning – Interpretable/Causal Deep Learning

Causal Graphical Models (CGMs)

- Directed Acyclic Graphs (DAGs) or Bayesian Networks (“acyclic” part $\rightarrow$ no loops, flow in one direction without cycling back)



$$p(X_1, X_2, X_3) = p(X_1)\, p(X_2 \mid X_1)\, p(X_3 \mid X_1, X_2)$$

Source: FAU Erlangen-Nuremberg, Pattern Recognition Lab, K.Breininger, V. Christlein, Advanced Deep Learning – Interpretable/Causal Deep Learning

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Causal Graphical Models (CGMs)

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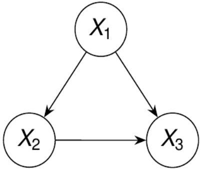

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Deep Learning Strategies – Part III
Causal Learning

Causal Graphical Models (CGMs)

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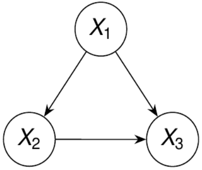

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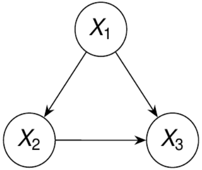

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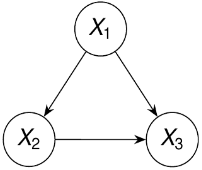
- Variables X (observations) as nodes and causal relationships between them as directed edges
- Causal Markov condition (Causal Independence!): $P(X_1, ..., X_n) = \prod_{i=1}^{n} P(X_i|PA_i)$, with PA_i as the parents of X_i, having a direct causal link (e.g. $X_1 \rightarrow X_2$)



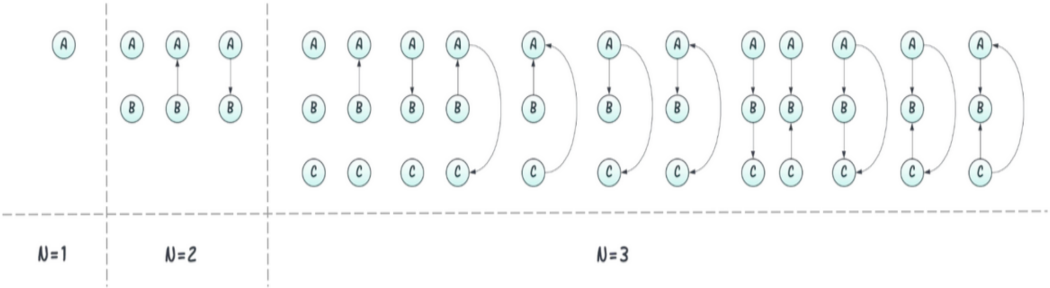
$$p(X_1, X_2, X_3) = p(X_1)\, p(X_2 \mid X_1)\, p(X_3 \mid X_1, X_2)$$

check it out again markov assumption

Source: FAU Erlangen-Nuremberg, Pattern Recognition Lab, K.Breininger, V. Christlein, Advanced Deep Learning – Interpretable/Causal Deep Learning

Space of causal graphs (i.e. DAGs) grows **super-exponentially.**

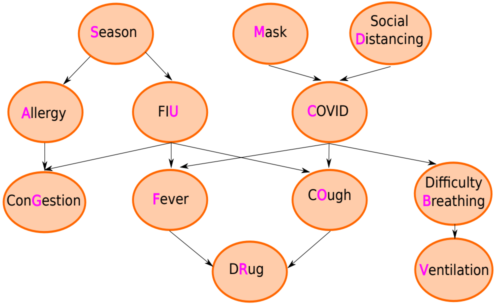
combination of all the directions



Source: Image from Nan Rosemary Ke, Stefan Bauer, "Causality and Deep Learning: Synergies, Challenges and the Future", Slide 26

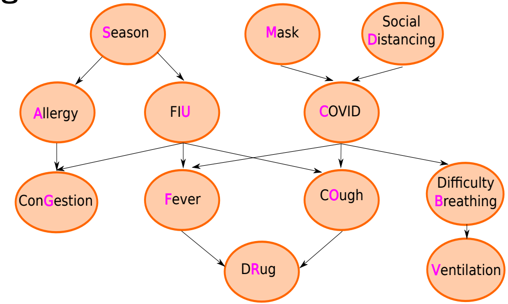
Bayesian Network

#	COVID	Mask	Soc. Distance	FIU	Cough	Fever	Ventilate	Season	ConGestion	Difficulty Breath	Drug	Allergy
1	1	0	1	0	1	0	1	Spring	0	0	1	0
2	0	1	0	1	0	1	0	Summer	1	1	0	0
3	1	1	1	0	0	0	1	Fall	1	0	1	1
4	0	0	1	1	1	0	0	Winter	0	1	0	0
...	...	...	...	...	...	...	...	...	...	...	...	...
500	0	1	1	1	0	0	0	Summer	0	0	1	1



Source: YouTube – easy learning – Causality 1: Bayesian networks are not causal, Link

Bayesian Network



- Random (dependent/independent) variables, e.g. Fever/COVID and Allergy/Cough

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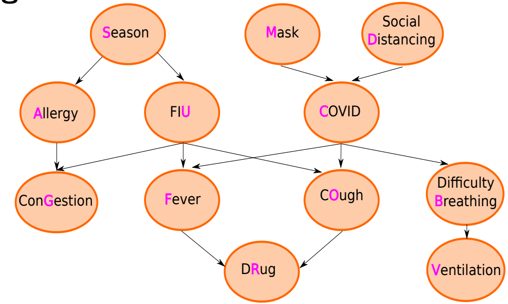
Bayesian Network



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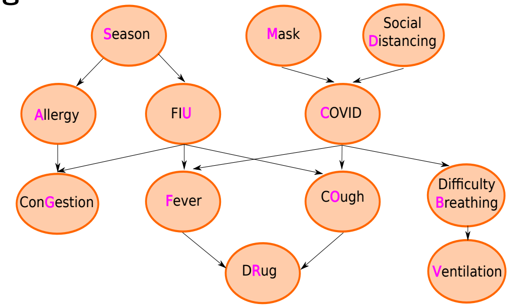
Bayesian Network



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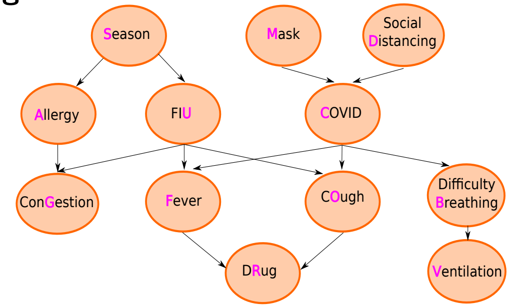

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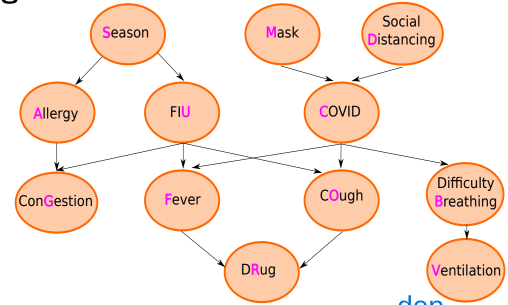
Deep Learning Strategies – Part III

Causal Learning

Bayesian Network



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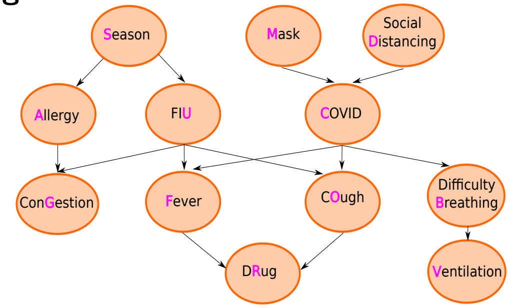
- How to read statistical dependence as causal dependence?

Source: YouTube – easy learning – Causality 1: Bayesian networks are not causal, Link

Bayesian Network



- In general: read a conditional probability $P(X|Y_1, ..., Y_n) \neq P(X)$, as X is "caused" by $Y_1, ..., Y_n$

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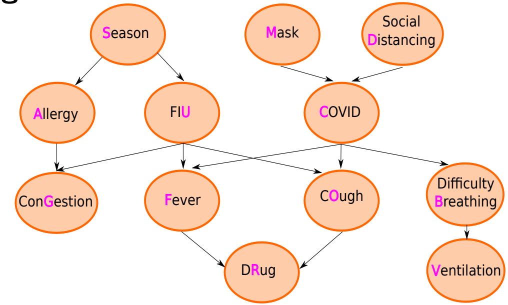
Deep Learning Strategies – Part III

Causal Learning

Bayesian Network



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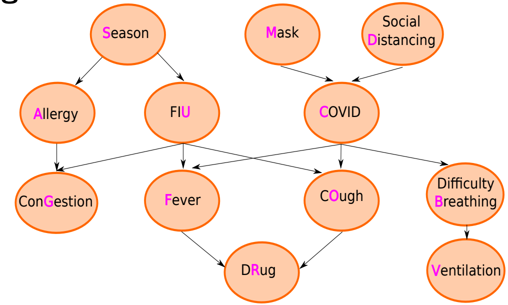
Deep Learning Strategies – Part III

Causal Learning

Bayesian Network



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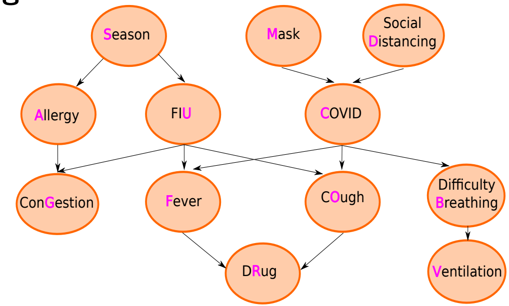

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- Still: No Causality!
- Goal: Given data D, what is causing what (the other)?

if we put p(x)=1 it means x does not have anything to fo with the effect

Source: YouTube – easy learning – Causality 1: Bayesian networks are not causal, Link

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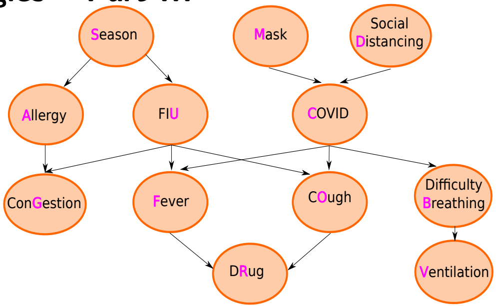
Bayesian Network



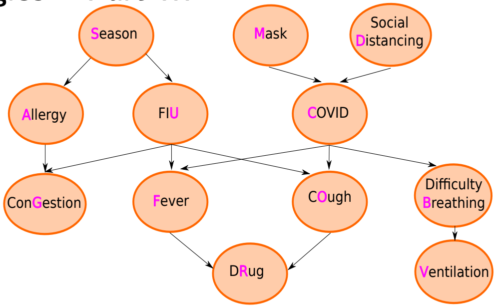
- Consider binary variables COVID $\in$ {COVID, ¬COVID} and Fever $\in$ {Fever, ¬Fever}

Source: YouTube – easy learning – Causality 2: Intervention, Link

Deep Learning Strategies – Part III

Causal Learning

Bayesian Network



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$$P(\text{Fever}|\text{COVID}) > P(\text{Fever}|\text{–COVID})$$

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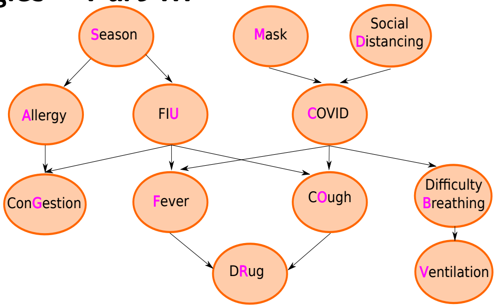
Bayesian Network



here we know there is some corelation but we dont know what is the corelation

if we add more data it is still in observeing mode we have to intervein to check what causes what

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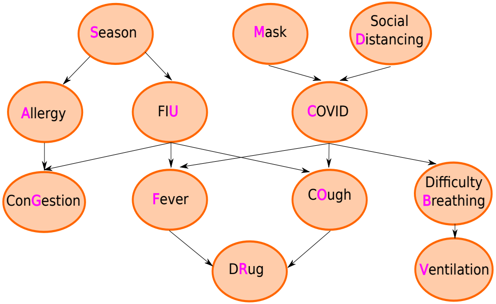
- Observing one of them, increases probability of the other! $\rightarrow$ Statistical dependence (correlation!) – Which one causes the other, how to figure it out – more data?

Source: YouTube – easy learning – Causality 2: Intervention, Link

Observation vs. Intervention



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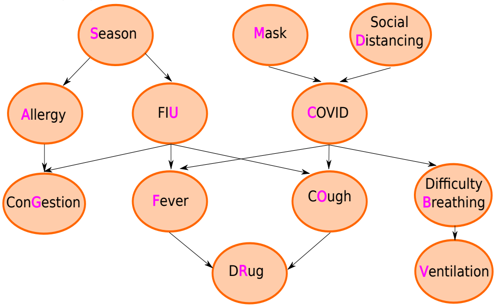

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- Why??? – How do we know that COVID is causing ($\rightarrow$) Fever and not vice versa?

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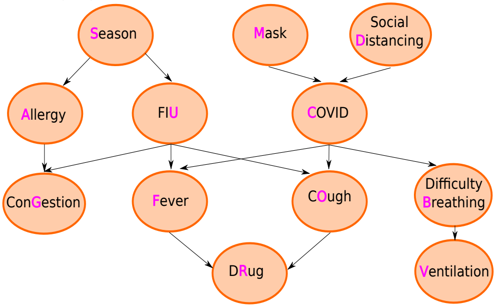

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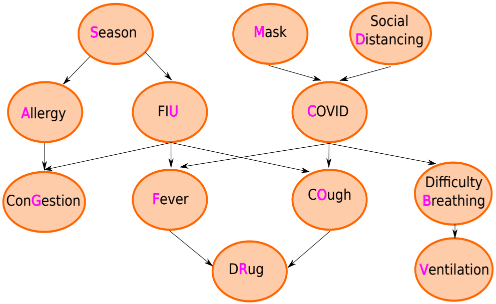
Deep Learning Strategies – Part III

Causal Learning

Observation vs. Intervention



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Source: YouTube – easy learning – Causality 2: Intervention, Link

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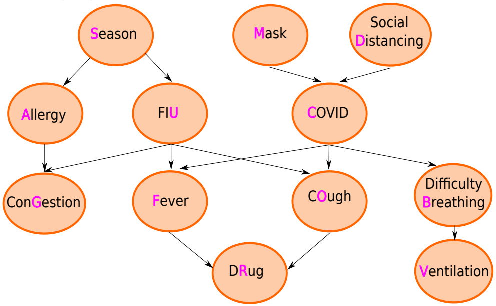

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- Force variables to certain values and check changes in the other variable
- Intervention $\rightarrow$ Causality!!! (...Find causal relationships)

Source: YouTube – easy learning – Causality 2: Intervention, Link

Intervention – Do-Operator

- Definition "Intervention": an ideal intervention on a given random variable Z is described by forcing its value to z, denoted $\mathrm{do}(Z := z)$ or $\mathrm{do}(z)$

Source: YouTube – easy learning – Causality 2: Intervention, Link

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Source: YouTube – easy learning – Causality 2: Intervention, Link

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- $\mathrm{do}(\mathrm{COVID} := 1)$ or $\mathrm{do}(\mathrm{COVID} := 0) \rightarrow$ Expectation: affect the likelihood of Fever, because COVID is a cause of fever (being the effect/sympotme of COVID)

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Intervention – Do-Operator

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when z=z
observation

- $P(Y|Z = z) \rightarrow$ Probability of Y, given that Z is seen/observed equals to z
- Constraint: when intervening on one variable, no other variable should be intervened
- do(COVID := 1) or do(COVID := 0) $\rightarrow$ Expectation: affect the likelihood of Fever, because COVID is a cause of fever (being the effect/sympotme of COVID)
- do(Fever := 1) or do(Fever := 0) $\rightarrow$ Expectation: does not affect the likelihood of COVID, because Fever is NOT a cause of COVID (not a sympotme of Fever)

Source: YouTube – easy learning – Causality 2: Intervention, Link

- Intervene on Fever (induce/remove fever) and observe COVID (person has/has not COVID), should not result in any probability difference of seeing/causing COVID:

  $$P(\mathrm{COVID}|\mathrm{do}(\mathrm{Fever})) = P(\mathrm{COVID}|\mathrm{do}(-\mathrm{Fever}))$$

  indicating that Fever does not cause COVID!

  $$P(\mathrm{COVID}|\mathrm{see}(\mathrm{Fever})) > P(\mathrm{COVID}|\mathrm{see}(-\mathrm{Fever}))$$

  Different from the observational relation!

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indicating that Fever does not cause COVID!

see is observation

$$P(\text{COVID}|\text{see}(\text{Fever})) > P(\text{COVID}|\text{see}(\neg\text{Fever}))$$

Different from the observational relation!

- However: intervene on COVID and observe Fever, lead to:

$$P(\text{Fever}|\text{do}(\text{COVID})) > P(\text{Fever}|\text{do}(\neg\text{COVID}))$$

COVID causes Fever!

$$P(\text{Fever}|\text{COVID}) > P(\text{Fever}|\neg\text{COVID})$$

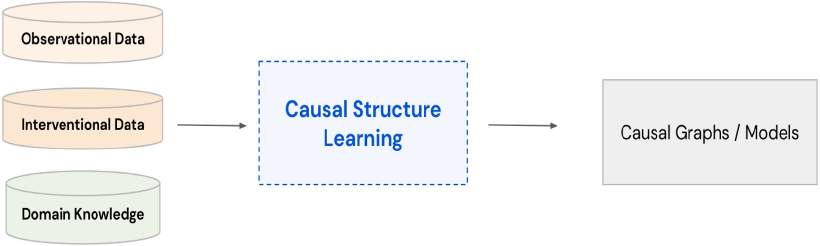
Interventional and observational relation is in line!

here the samples are idd and that is why we have rfealtion betwween covid and fever

Source: YouTube – easy learning – Causality 2: Intervention, Link

Deep Learning Strategies – Part III

Causal Learning



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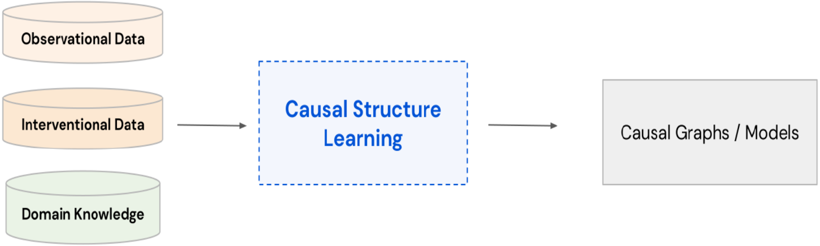
Deep Learning Strategies – Part III

Causal Learning



- Observational Data: collected without actively manipulating variables, just observing the natural state of the system (correlations/associations)
- Interventional Data: collected by actively changing or intervening on specific variables, to reveal causal relationships

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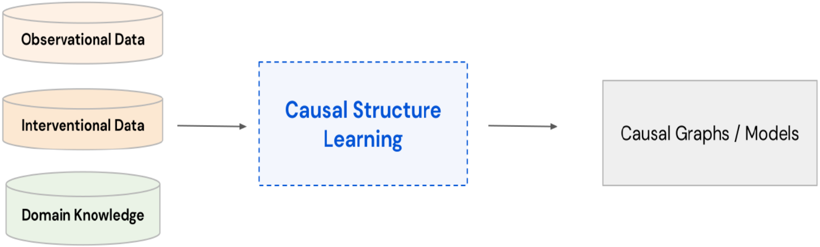
Deep Learning Strategies – Part III

Causal Learning



- Observational Data: collected without actively manipulating variables, just observing the natural state of the system (correlations/associations)
- Interventional Data: collected by actively changing or intervening on specific variables, to reveal causal relationships
- Domain Knowledge: includes expert understanding, assumptions, or prior information about the system being studied, to help guiding the interpretation of observational data and the design of meaningful interventions

Source: FAU Erlangen-Nuremberg, Pattern Recognition Lab, K.Breininger, V. Christlein, Advanced Deep Learning – Interpretable/Causal Deep Learning

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- Average Causal Effect (ACE): Binary variable $Z \in \{0, 1\}$, causes variable Y, if the average causal effect (ACE) of Z on $Y = y$ is defined as:

$$ACE(Z \rightarrow Y_y) = P(Y = y|\mathrm{do}(Z := 1)) - P(Y = y|\mathrm{do}(Z := 0))$$

  is non-zero!

Source: YouTube – easy learning – Causality 3: Defining causality: Structural causal models (SCM), Link

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$$P(Y|\text{do}(z_0)) \neq P(Y|\text{do}(z_1))$$

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is non-zero! if it is zero then their is no casual effect intrepret with previous slides

- Causality: A variable Z causes variable Y if there exist two interventional events z_0 and z_1 changing the distribution Y:

$$P(Y|\mathrm{do}(z_0)) \neq P(Y|\mathrm{do}(z_1))$$

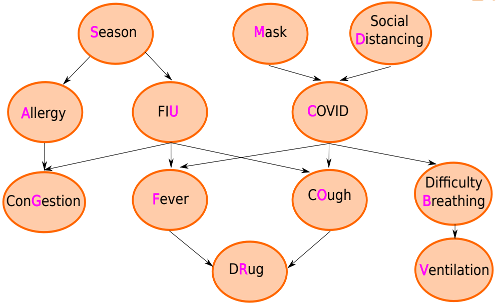
- However: Let $Y = X \oplus Z$ be the XOR-Function of X and Z, then:

$$P(Y|\mathrm{do}(X = 0)) = P(Y|\mathrm{do}(X = 1)) = P(Y)$$ check this formulla

$\rightarrow$ Better Definition as Deterministic Function!

Source: YouTube – easy learning – Causality 3: Defining causality: Structural causal models (SCM), Link

Causality as Deterministic Function!



- COVID is the cause of Cough and Cough is the cause of Drug → More factors, however not being explicitly modeled and represented as single exogenous (latent variable) U_X

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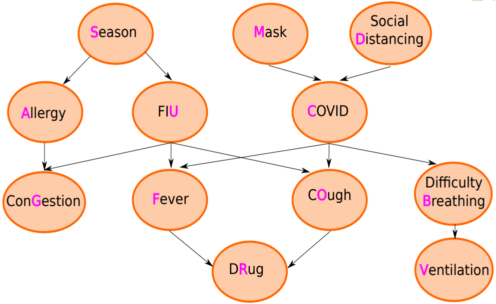

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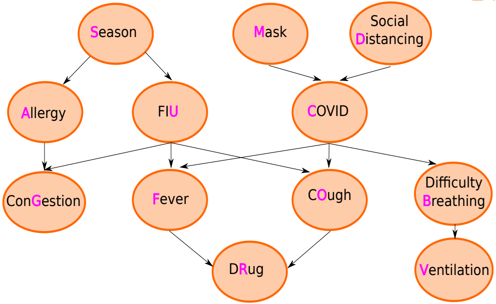

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- Each Variable X (here: C, O, R – referred to as endogenous) have such exogenous (here: U_C, U_O, U_R) variables, used together with a deterministic function of is endogenous and exogenous parents
- $C := f_C(U_C) = U_C$, $O := f_O(C, U_O)$, $R := f_R(O, U_R)$
  $\rightarrow$ Structural Causal Model (SCM)

Source: YouTube – easy learning – Causality 3: Defining causality: Structural causal models (SCM), Link

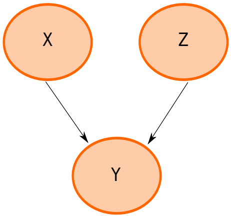
Structural Causal Models (SCMs)

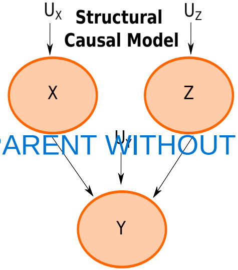
- SCM defined as a touple $< V, U, P_U, F >$ with:

1. V as the set of endogenous random variables
2. $U = \{U_X | X \in V\}$ as set of exogenous/latent/noise random variables
3. P_U is the joint distribution over U satisfying $P_U(U) = \prod_X P_U(U_X)$
4. F set of functions f_X, how values are assigned to each variable $X \in V$, based on a subset of endogenous variables $Pa_X \subset V \setminus \{X\}$ (parents), with a parent exogenous variable $U_X \subset U$, leading to:

$$X := f_X(Pa_X, U_X)$$

Causal Network





PAX IS PARENT WITHOUT X

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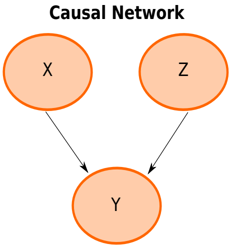
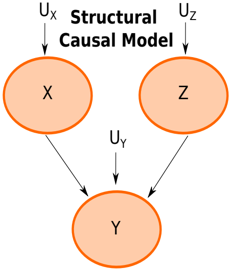
- Causal graph (network) over nodes V, where the parents of each node are linked to it (assume the graph as DAG)





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Causal Learning

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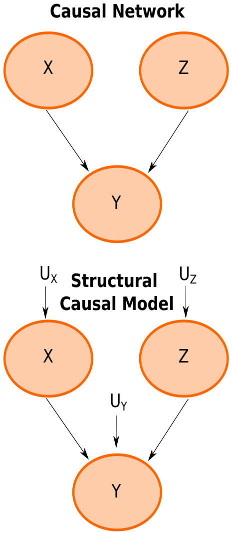

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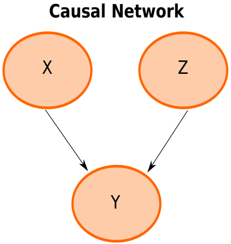

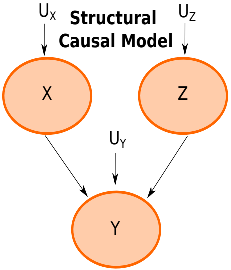

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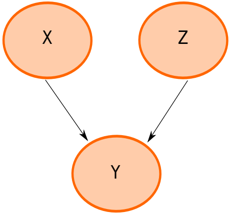
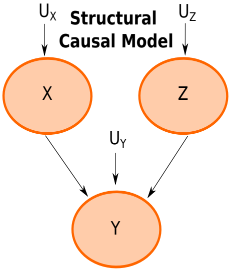
Causal Network



Structural Causal Model



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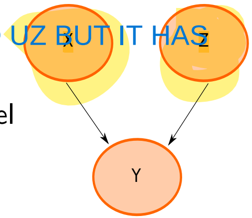
Structural Causal Models (SCMs)

Y DOENT CARE ABOUT UX AND UZ BUT IT HAS EFFECTED BY UY



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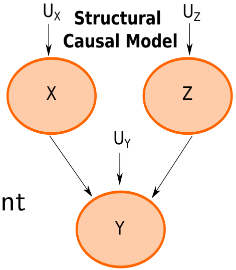
- Observational distribution of all endogenous variables V refers to the joint probability distribution $P(V) = \prod_X P(X|Pa_X)$



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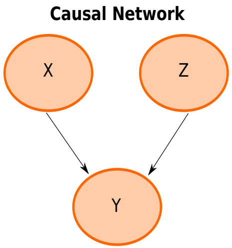
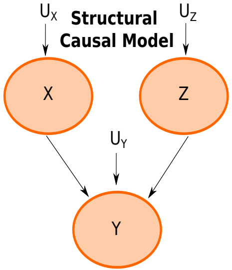
Structural Causal Models (SCMs)

- The causal network $\mathcal{G}$ is an I-Map for $P(V) = \prod_X P(X|Pa_X)$ (Bayesian Network Factorization) with $P(X|Pa_X)$ obtained from $X = f_X(Pa_X, U_X)$





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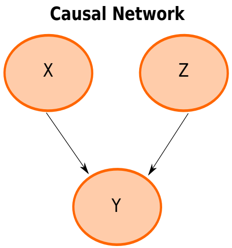

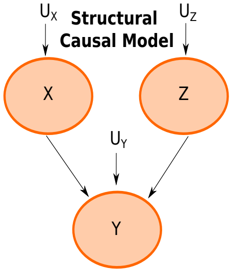

Deep Learning Strategies – Part III

Causal Learning

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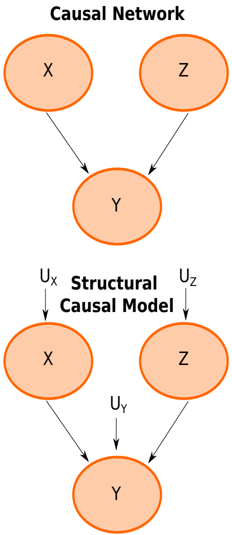

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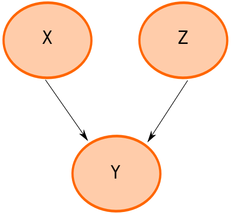
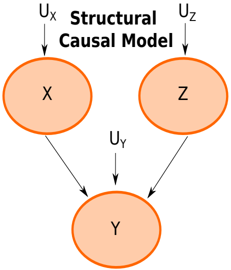


Structural Causal Model



Deep Learning Strategies – Part III

Causal Learning

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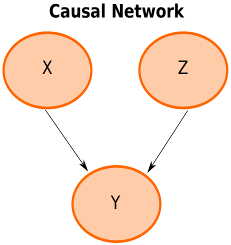
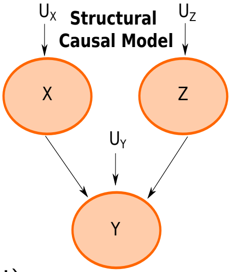
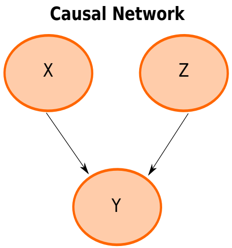
- Example I-MAP Graph: $X \rightarrow Y \rightarrow Z$ – with $X =$ Having Disease, $Y =$ Taking Medication, $Z =$ Observing Side Effects
- Captures direct dependencies ($X \rightarrow Y$, $Y \rightarrow Z$) and conditional independencies (X and Z are independent given Y, disease X alone not directly lead to side effects Z, only through the medication Y – parents!!!)

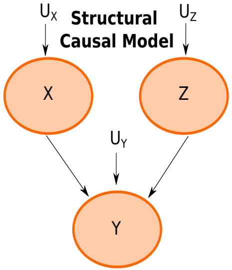




Structural Causal Models (SCMs) – Example XOR

- $P(V) = P(X = x, Z = z, Y = y)$





Source: YouTube – easy learning – Causality 3: Defining causality: Structural causal models (SCM), Link

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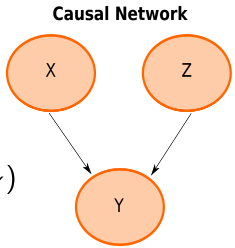

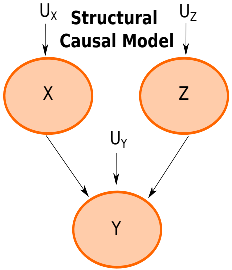

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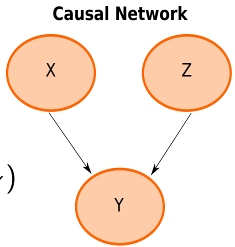

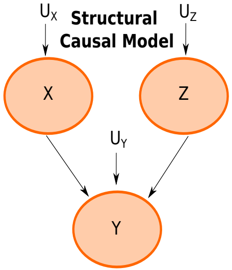

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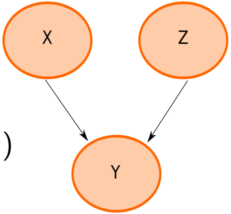
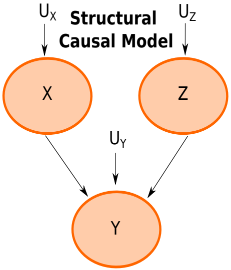
Causal Network



Structural Causal Model



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x and z jas only ux and uz aas pafents

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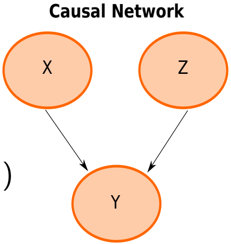
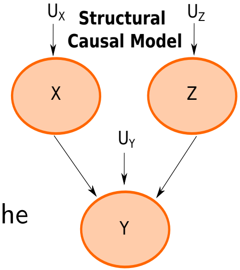
xor operation here

- Note: From an SCM it is possible to compute the joint distribution of the given variables!





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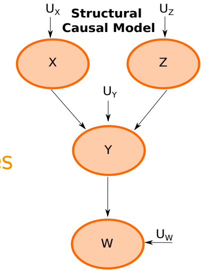
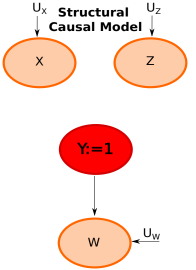
Structural Causal Models (SCMs) – Example XOR – Intervention

- Causal network turns into a Bayesian network if augmented with CPDs (prior probabilities, conditional probabilities) answering probability queries $P(Y|Z=z)$ for all $z \in Val(Z)$, $Z, Y \subseteq V$





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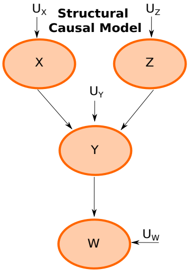
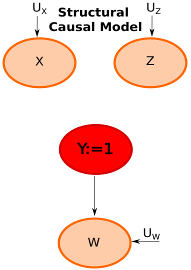
- Conditional Probability Distribution (CPD): function that defines the probability of a random variable, given the values of its parent variables in a graph $P(X|Pa_X)$





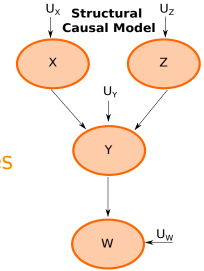
Source: YouTube – easy learning – Causality 3: Defining causality: Structural causal models (SCM), Link

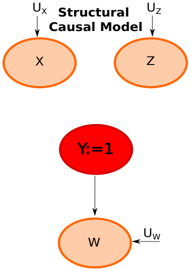
Structural Causal Models (SCMs) – Example XOR – Intervention

- Causal network turns into a Bayesian network if augmented with CPDs (prior probabilities, conditional probabilities) answering probability queries $P(Y|Z = z)$ for all $z \in Val(Z)$, $Z, Y \subseteq V$
- Conditional Probability Distribution (CPD): function that defines the probability of a random variable, given the values of its parent variables in a graph $P(X|Pa_X)$
- Intervention in SCMs (do-operation): setting $Y := 1$

  Before: $X := U_X,\ Z := U_Z,\ Y := X \oplus Z + U_Y,\ W := 2Y + U_W$

  After: $X := U_X,\ Z := U_Z,\ Y := 1,\ W := 2Y + U_W \rightarrow U_W = W - 2$





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Deep Learning Strategies – Part III

Causal Learning

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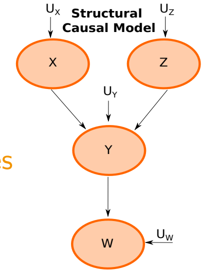
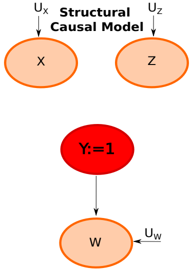
- Y does not depend on its endogenous/exogenous parents Pa_Y (all incoming links in the graph are removed!) $\rightarrow$ Perfect intervention!

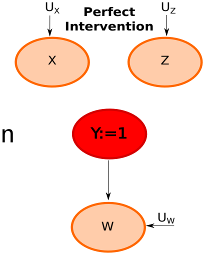


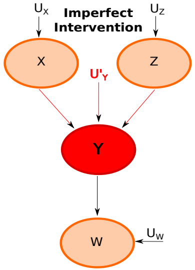


Source: YouTube – easy learning – Causality 3: Defining causality: Structural causal models (SCM), Link

Structural Causal Models (SCMs) – Example XOR – Intervention

- In a perfect intervention the variable Y has a fixed/static value, based on its intervened value





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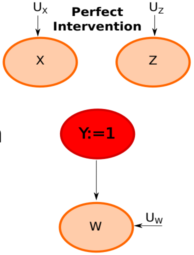
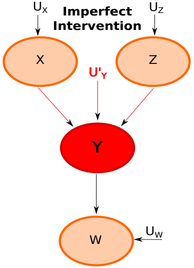
Structural Causal Models (SCMs) – Example XOR – Intervention

- In a perfect intervention the variable Y has a fixed/static value, based on its intervened value
- However: there exist also an imperfect/parametric intervention, known as mechanism change (f' assignment) (still some remaining parents) → $Y := f(Pa_Y, U_Y) \rightarrow Y := f'(Pa_Y, U'_Y)$ (e.g. $Y := X - Z + U'_Y$)





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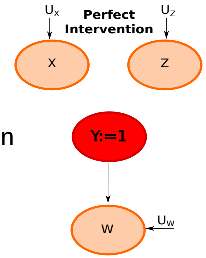

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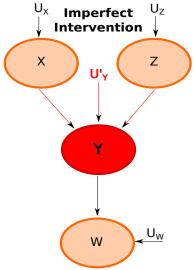
- Every intervention leads to a CPD change w.r.t. Y from:

  $Y : P(Y|Pa_Y)$ to $P^{\star}(Y|Pa_Y)$



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Structural Causal Models (SCMs) – Example XOR – Intervention

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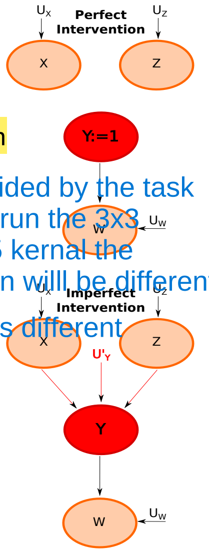
- Every intervention leads to a CPD change w.r.t. Y from:

  $Y : P(Y|Pa_Y)$ to $P^{\star}(Y|Pa_Y)$
- After every intervention there exist still a (new) SCM (causal network), with different dependencies and a intervention distribution $P(V \backslash Z, \mathrm{do}(Z))$ a intervention distribution over all the variables V

function is decided by the task
e.gg when we run the 3x3 kernal and 5x5 kernal the causual realtion willl be different

change y as different fucntion



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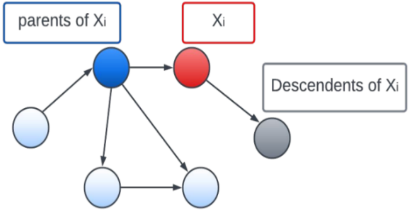
summary slide

Describing the causal mechanisms of a system.



- **Variables:** $\mathbf{X} = \{X_1, \ldots, X_N\}$
- **Noise:** $U = \{U_1, \ldots, U_N\}$
- **Causal parents of Xi** $X_{pa(i,G)}$
- **Structural Equations:** (Causal Mechanisms) $X_i = f_i\left(X_{pa(i,\mathbf{G})}, U_i\right) \quad \forall i \in \{1, \ldots N\}$

Source: Image from Nan Rosemary Ke, Stefan Bauer, "Causality and Deep Learning: Synergies, Challenges and the Future", Slide 22

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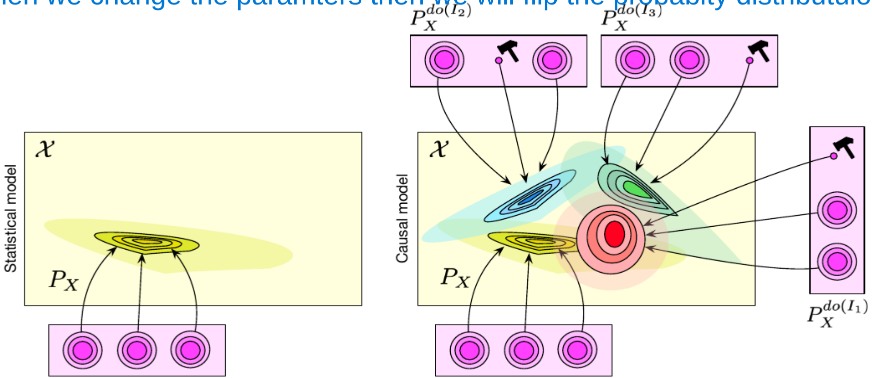
Causal Learning

when we change the paramters then we will flip the probablty distributuion



- Statistical (Bayesian) Model: can only capture one probability distribution
- Causal Model: every intervention defines new joint distribution intervention

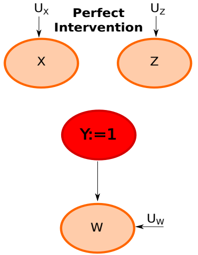
Source: FAU Erlangen-Nuremberg, Pattern Recognition Lab, K.Breininger, V. Christlein, Advanced Deep Learning – Interpretable/Causal Deep Learning

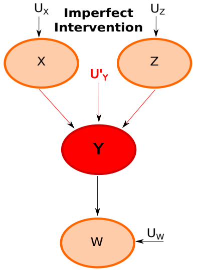
Source: Image from Nan Rosemary Ke, Stefan Bauer, "Causality and Deep Learning: Synergies, Challenges and the Future", Slide 22

Source: Schölkopf et al., "Toward Causal Representation Learning"

Structural Causal Models (SCMs) – Example XOR – Mutilated Network

- Converting an intervention to an observation query (remove all do's)

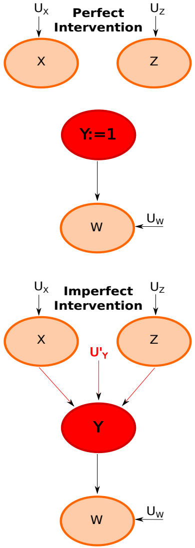




Source: YouTube – easy learning – Causality 3: Defining causality: Structural causal models (SCM), Link

Structural Causal Models (SCMs) – Example XOR – Mutilated Network

- Converting an intervention to an observation query (remove all do's)
- In case of the previous Bayesian Network, and for a perfect intervention query, $P(Y|\text{do}(z), x)$ is transformed to $P(Y|z, x)$, by removing all incoming edges to the intervened nodes Z, and set a fixed intervention value $Z = z$



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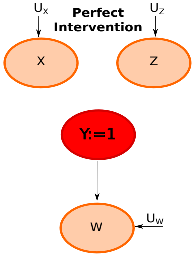
Structural Causal Models (SCMs) – Example XOR – Mutilated Network



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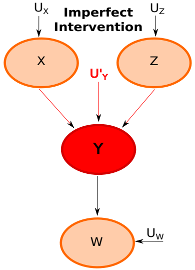
- Mutilated Network: $\mathcal{B}_{Z:=z}$, given a Bayesian Network $\mathcal{B}$, while removing all incoming links to the set of nodes Z and setting $Z = z$ (static value), $P(Z = z') = 1$ if $z' = z$, otherwise 0



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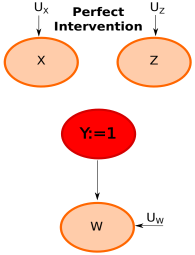

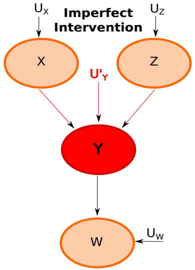

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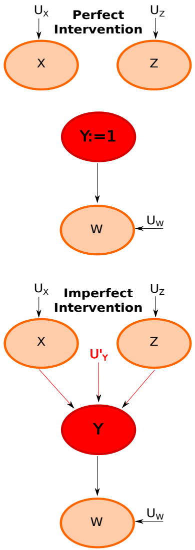
- Answering intervention queries: $P(Y|\text{do}(z), x) = P_{\mathcal{B}_{Z:=z}}(Y|z, x)$
- Modularity: conditional probability of a node is only affected if intervention is on its parents $P(Y|Pa_Y, \text{do}(z)) = P(Y|Pa_Y), \ \forall Y \notin Z$



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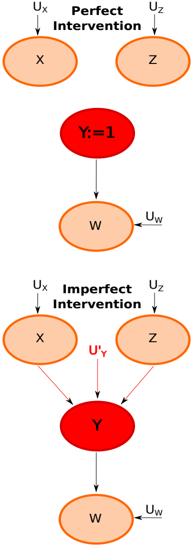
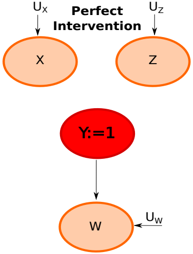
Structural Causal Models (SCMs) – Example XOR – Causal (Bayesian) Model

- Causal (Bayesian) Network $\mathcal{C}$ (CBN): over a set of random variables V (joint distribution P), $\mathcal{C}$ is a Bayesian network $\mathcal{B}(\mathcal{G}, P_{\mathcal{C}})$, with $\mathcal{G}$ is an I-Map for P, over V, answering both probability queries:
  1. $P(Y|x) = P_{\mathcal{C}}(Y|x)$ and intervention queries:
  2. $P(Y|Pa_Y, \mathrm{do}(z)) = P_{\mathcal{C}_{Z:=z}}(Y|Pa_Y), \ \forall Y \notin Z, \ z \in \mathrm{Val}(Z)$



Source: YouTube – easy learning – Causality 4: Causal Bayesian Networks, Link

Structural Causal Models (SCMs) – Example XOR – Causal (Bayesian) Model



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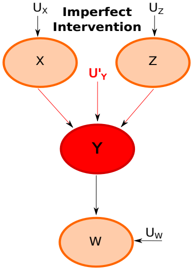
- Recap: Causal Hierarchy

1. Association (Seeing!) – Probabilistic query $P(Y|X)$ (e.g. probability of developing cancer given that the individual smokes?) – BN, CBN, SCM
2. Intervention (Doing!) – Invervention query $P(Y|\mathrm{do}(X))$ (e.g. What is the prob. of developing cancer if individuals stop smoking?) – CBN, SCM
3. Counterfactual (Imagining!) – Counterfactual query $P(Y_{X=1}|X=0)$ (e.g. What would have happpened if individuals had quitted smoking?) – SCM



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Structural Causal Models (SCMs) – Counterfactual Queries

- Bayesian Network (BN) is able to answer probabilistic queries (associations), while Causal Bayesian Networks (CBN) & SCM can also handle intervention queries

Source: YouTube – easy learning – Causality 6: Counterfactual Queries, Link

Structural Causal Models (SCMs) – Counterfactual Queries

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- What about the last topic, addressing counterfactual queries?

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- Example: There was a fork in the road, where a decision must be made – take the freeway ($X = 1$) or go on a surface street ($X = 0$). The person took the surface street with a lot of traffic and arrived one hour later ($Y = 1$). He asked hisself – If he had taken the freeway, he would have gotton home earlier!!!

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- Such an unrealized situation from the past, wrapped in an "if-statement" is known as counterfactual $\rightarrow$ How to model a counterfactual query/situation?

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Structural Causal Models (SCMs) – Counterfactual Queries

- Let Y be the arriving time ($Y = 1$ for being late, $Y = 1$ for being in time)

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Structural Causal Models (SCMs) – Counterfactual Queries

- Let Y be the arriving time ($Y = 1$ for being late, $Y = 1$ for being in time)
- Causal inference: prediction of Y from the past, by intervening on the road (change from surface road $X = 0$ to freeway $X = 1$): $P(Y|\text{do}(X = 1))$

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- Counterfactual problem: asking about Y, if we had forced $X := 1$ in the past observed event with $X = 0, Y = 1 \rightarrow$ Clash regarding Y: $P(Y|\text{do}(X = 1), Y = 1, X = 0)$

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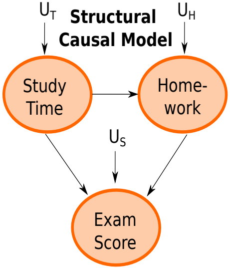
- Counterfactual inference: reformulate as: $P(Y_{X=1}|X = 0, Y = 1)$

Source: YouTube – easy learning – Causality 6: Counterfactual Queries, Link

Structural Causal Models (SCMs) – Counterfactual Queries

- Example Counterfactual Event:
  - $T := U_T, \quad H := 0.5T + U_H, \quad S := 0.7T + 0.4H + U_S$
    with: T as the students studying time, H as the number of completed homeworks, S student's exam score, U_T student's free time at home, U_H student's intelligence, U_S student's anxiety



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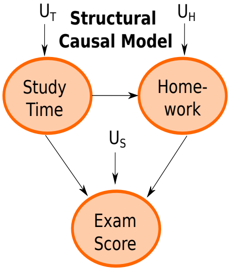
  - Let $T = 0.5$, $H = 1$, and $S = 1.5$ for a particular student, resulting in:
    $U_T := T = 0.5$, $U_H = H - 0.5T = 1 - 0.5 \cdot 0.5 = 0.75$,
    $U_S = S - 0.7T - 0.4H = 1.5 - 0.7 \cdot 0.5 - 0.4 \cdot 1 = 0.75$



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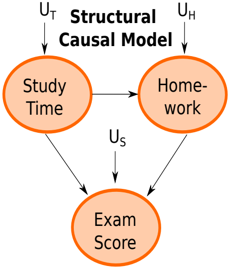
    $U_S = S - 0.7T - 0.4H = 1.5 - 0.7 \cdot 0.5 - 0.4 \cdot 1 = 0.75$
  - Counterfactual problem: what would the student's score have been if he had doubled his done homework?



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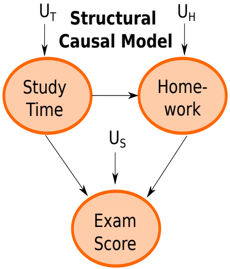
  - Counterfactual problem: what would the student's score have been if he had doubled his done homework?
  - Intervention: do-operator to $P(S|Pa_S, U_S) = P(S|T, \text{do}(H := 2), U_S)$



Source: YouTube – easy learning – Causality 6: Counterfactual Queries, Link

Structural Causal Models (SCMs) – Counterfactual Queries

- Example Counterfactual Event:
  - $T := U_T, \quad H := 0.5T + U_H, \quad S := 0.7T + 0.4H + U_S$
    with: T as the students studying time, H as the number of completed homeworks, S student's exam score, U_T student's free time at home, U_H student's intelligence, U_S student's anxiety
  - Let $T = 0.5$, $H = 1$, and $S = 1.5$ for a particular student, resulting in:
    $U_T := T = 0.5$, $U_H = H - 0.5T = 1 - 0.5 \cdot 0.5 = 0.75$,
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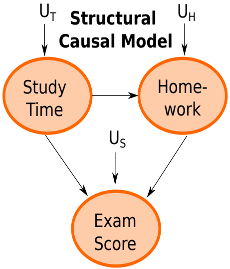
  - Counterfaction: $P(S_{H=2}|T = 0.5, H = 1, S = 1.5)$



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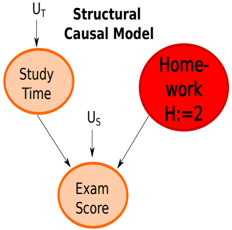
Structural Causal Models (SCMs) – Counterfactual Queries

- Example Counterfactual Event
  - Create mutilated graph, by removing all incoming links to the invervened node $Z = H$, with $P(H = 2) = 1$



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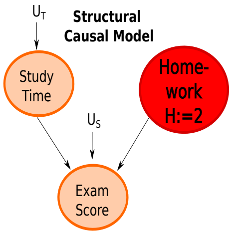

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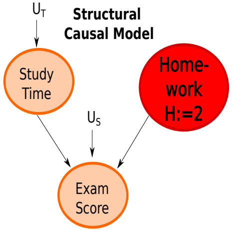
  1. Abduction – use evidence $E = e$ in order to determine all the values of U



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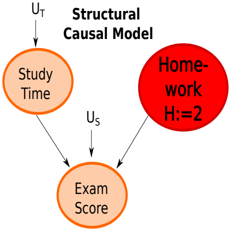

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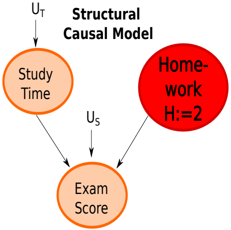

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  3. Prediction – Use the mutilated model and the value of U to compute the value of Y, the consequence of the counterfactual

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Summary – Difference BN, CBN and SCM

- Bayesian Network (BN)

1. BN is a directed acyclic graph (DAG) that represents probabilistic relationships among variables, while each random variable (node) connection represents a conditional dependence $\rightarrow$ No causation, only correlations, and conditional independencies

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2. Example: Bayesian Network, with nodes: Flu $\rightarrow$ Fever, Flu $\rightarrow$ Cough, while the model/graph shows the association between Flu and Fever, as well as Flu and Cough, however, no information that Flue causes both

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5. Example: same graph w.r.t. causation, show that Flu causes Fever and Cough, while intervening Flu causes an impact with resepct to Fever and Cough

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Summary – Difference BN, CBN and SCM

- Structural Causal Model (SCM)

1. SCM is a causal model providing a more formal framework than a CBN, using a set of structural equations that specify how each variable is generated as a function of its causal parents and some random “noise” term, along with a causal DAG structure

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2. SCMs allow for both causal inference and formal intervention analysis, while being used for counterfactual reasoning, interventions, and predicting causal effects
3. SCM would not only represent Flu causing Fever & Cough, but also provide equations – $\text{Fever}=f(\text{Flu}, U_F)$, $\text{Cough}=g(\text{Flu}, U_C)$ – specifying how Flu influences Fever & Cough under different conditions

Further Questions?

https://www.oth-aw.de/hochschule/ueber-uns/personen/bergler-christian/

Source: https://emekaboris.medium.com/the-intuition-behind-100-days-of-data-science-code-c98402cdc92c