

HWSW mobile! - APPLIED AI SECTION

'WHAT TO DO IF WE DON'T HAVE ENOUGH DATA?'

INTRO

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Presently:

Lecturer: Frankfurt School of Finance and Management, Specialization leader: KÜRT Academy,

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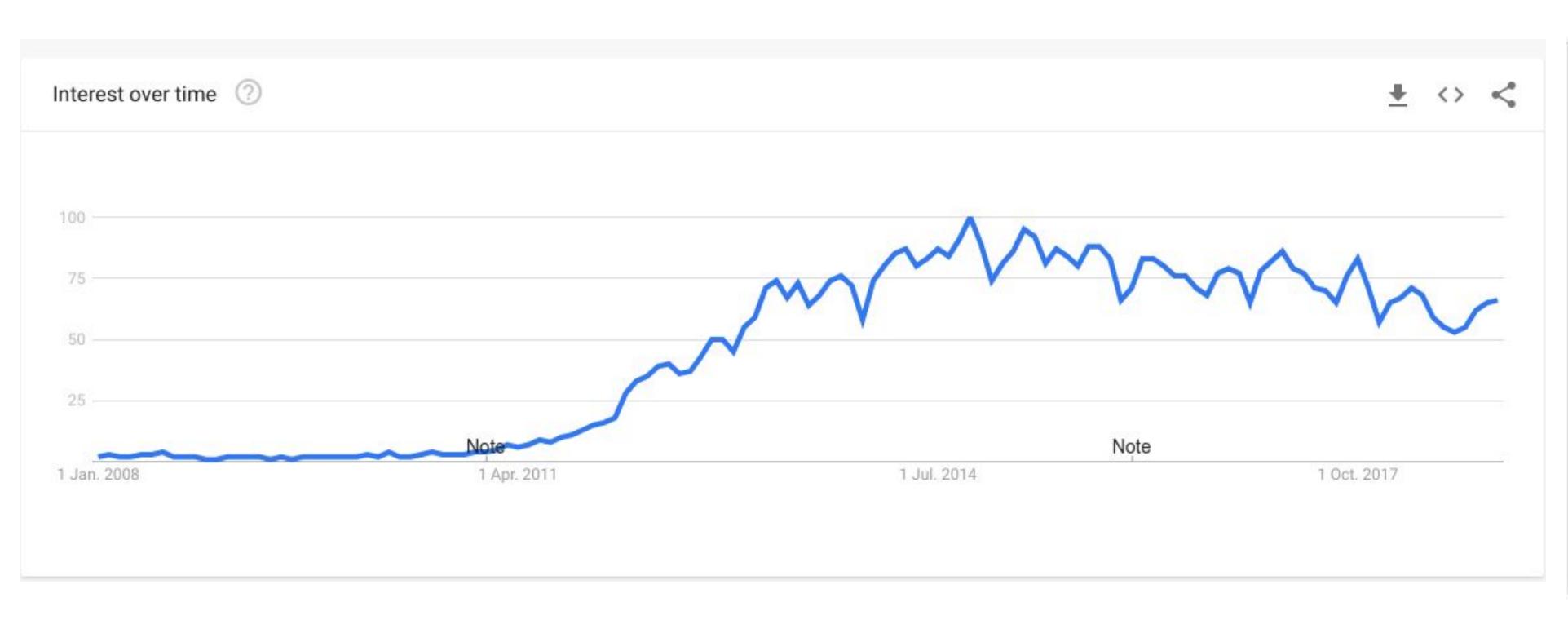
<u>CONTACT</u>

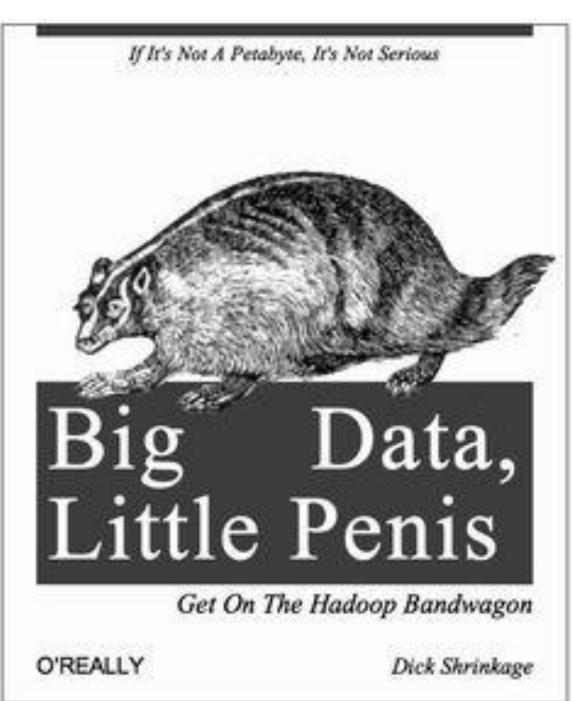






BIG DATA IS - NOT EVERYTHING - IS BIG DATA!





SMALL DATASETS VIOLATE BASIC ASSUMPTIONS

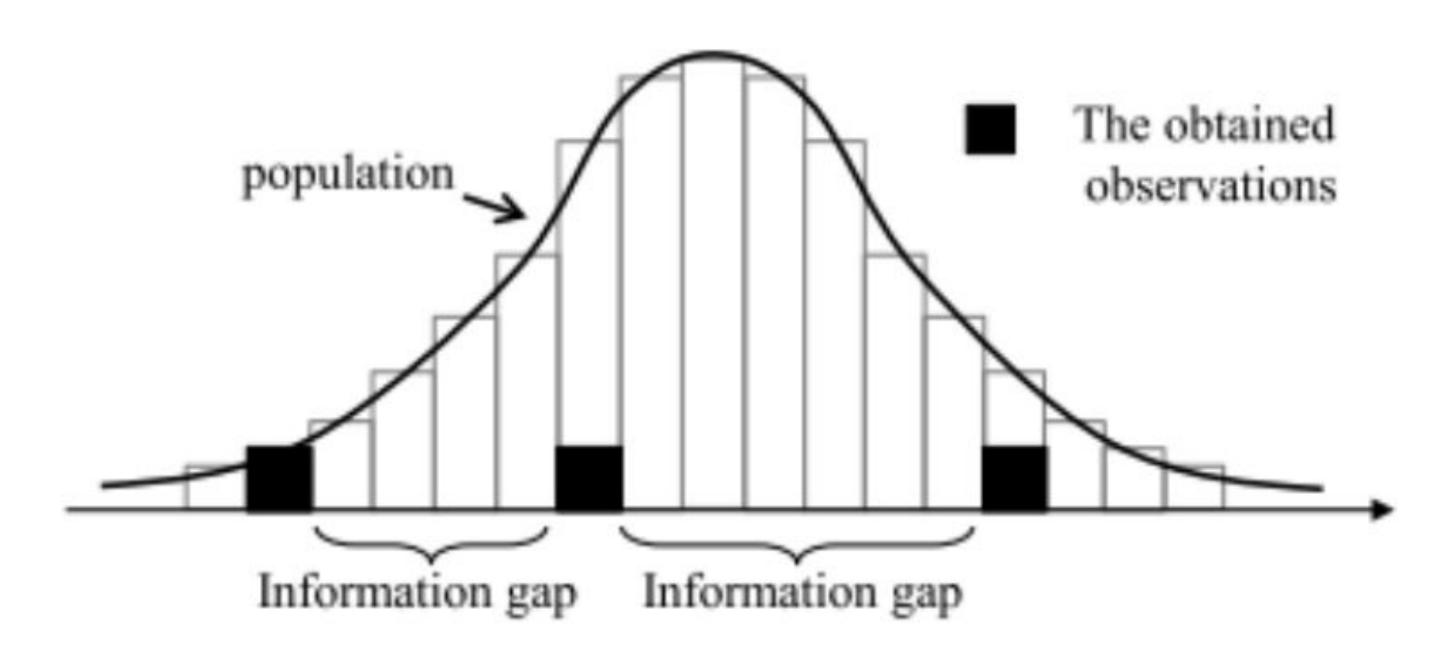
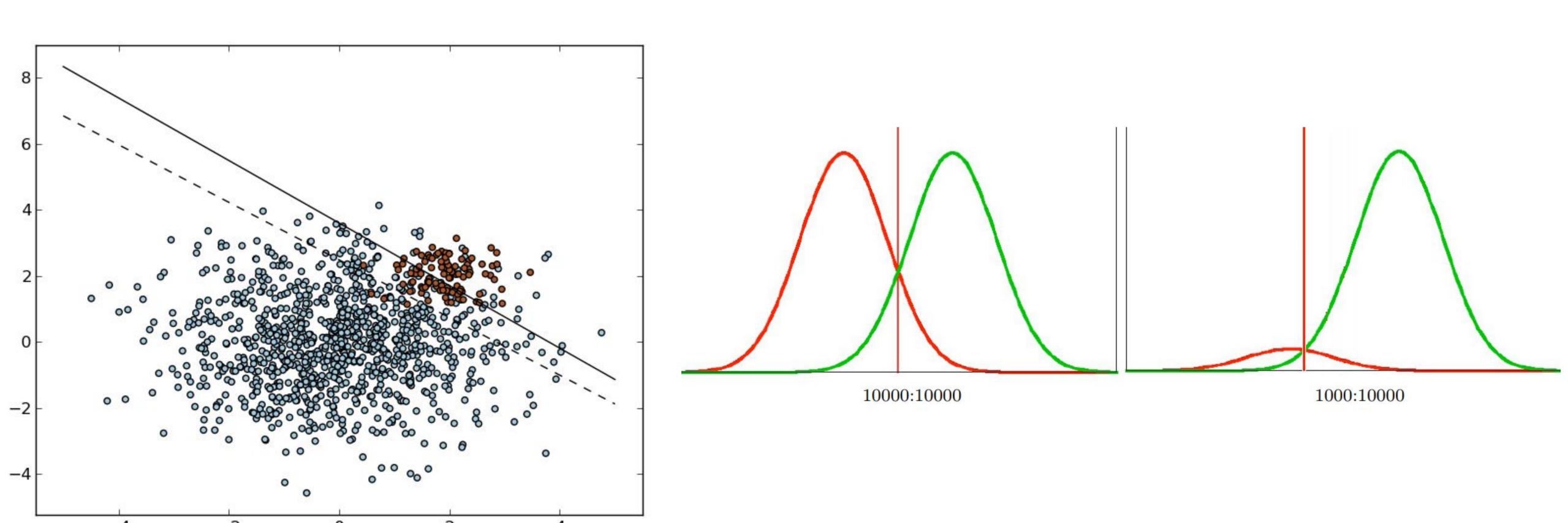


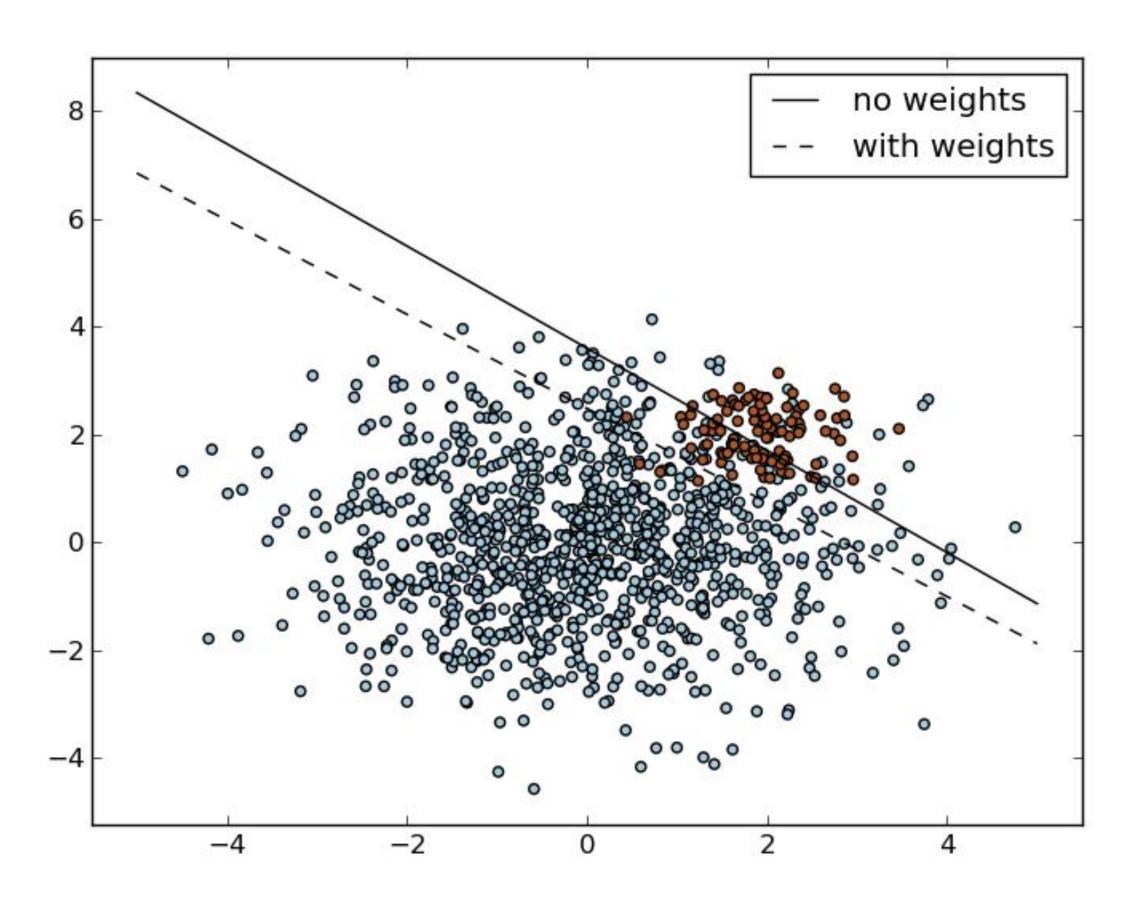
Figure 2. The distribution of a small dataset relative to its population [6]

CASE I. - WE DON'T HAVE ENOUGH OF ONE THING



source: <u>"Classification in imbalanced datasets"</u>

SOLUTION 1. - "COST SENSITIVE LEARNING"

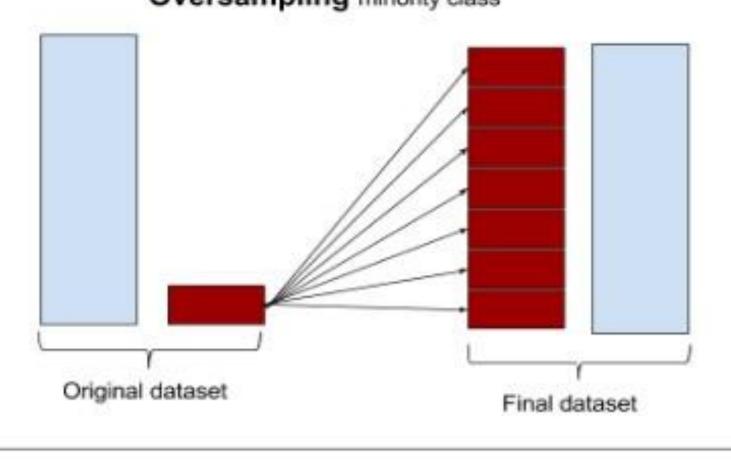


Predicted Actual	Category-A	Category-B
Category-A	90	0
Category-B	10	0

We can try to **modify our objective** / cost calculation to accommodate the fact, that making an error on the minority class is a "more serious issue".

SOLUTION 2. - "SAMPLING"

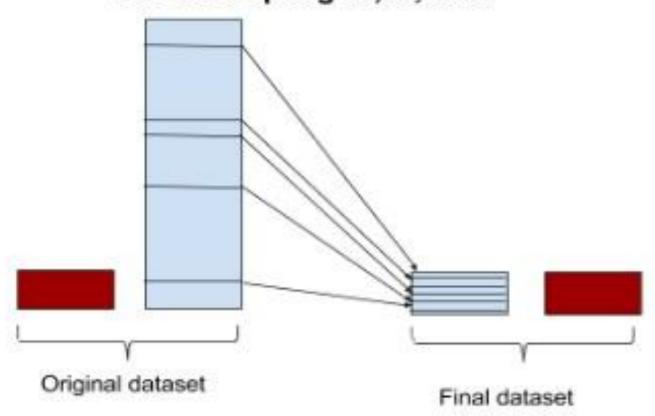
Oversampling minority class



- Undersampling:

- Choose only some of the majority class datapoints
- Reduces the overall dataset, **not recommended**

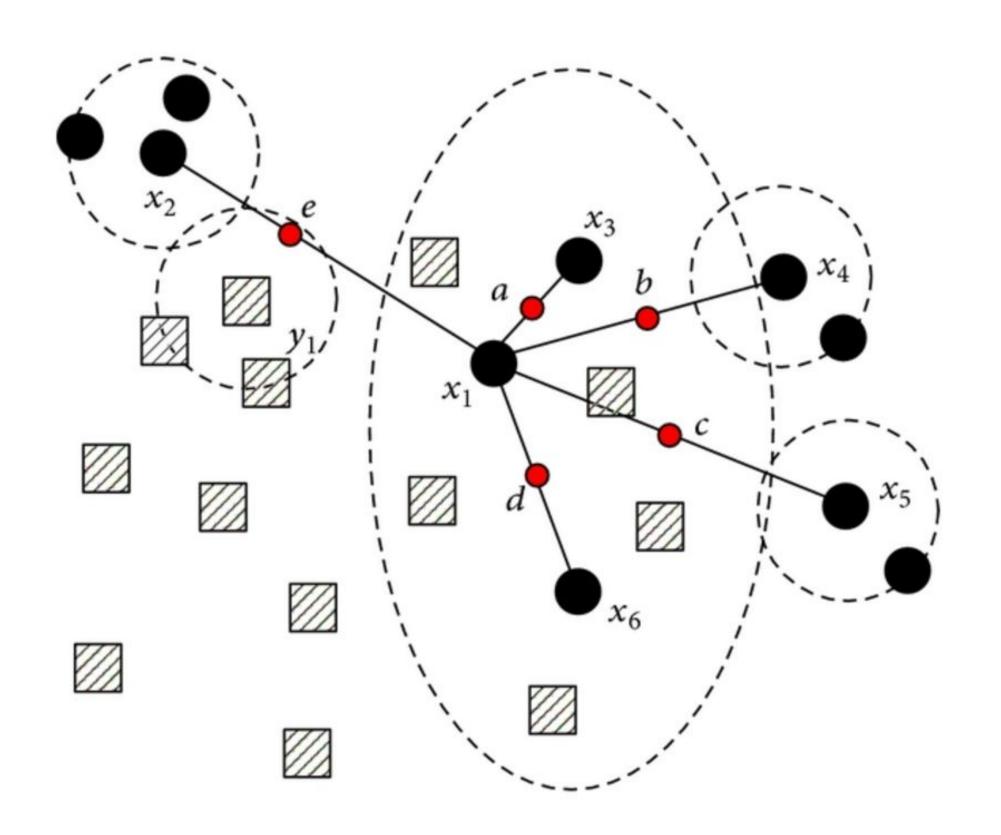
Undersampling majority class



Oversampling:

- Repeatedly use some of the minority class datapoints
- Good question is: Which ones?
 - Can we be more intelligent then random choice?

SOLUTION 3. - DATA SYNTHESIS



- Create new datapoints! (SMOTE)

"First it finds the n-nearest neighbors in the minority class for each of the samples in the class. Then it draws a line between the the neighbors an generates random points on the lines."

- ...and add some noise! (ADASYN)

"After creating those sample it adds a random small values to the points thus making it more realistic. In other words instead of all the sample being linearly correlated to the parent they have a little more variance in them i.e they are bit scattered."

- Majority class samples
- Minority class samples
- Synthetic samples

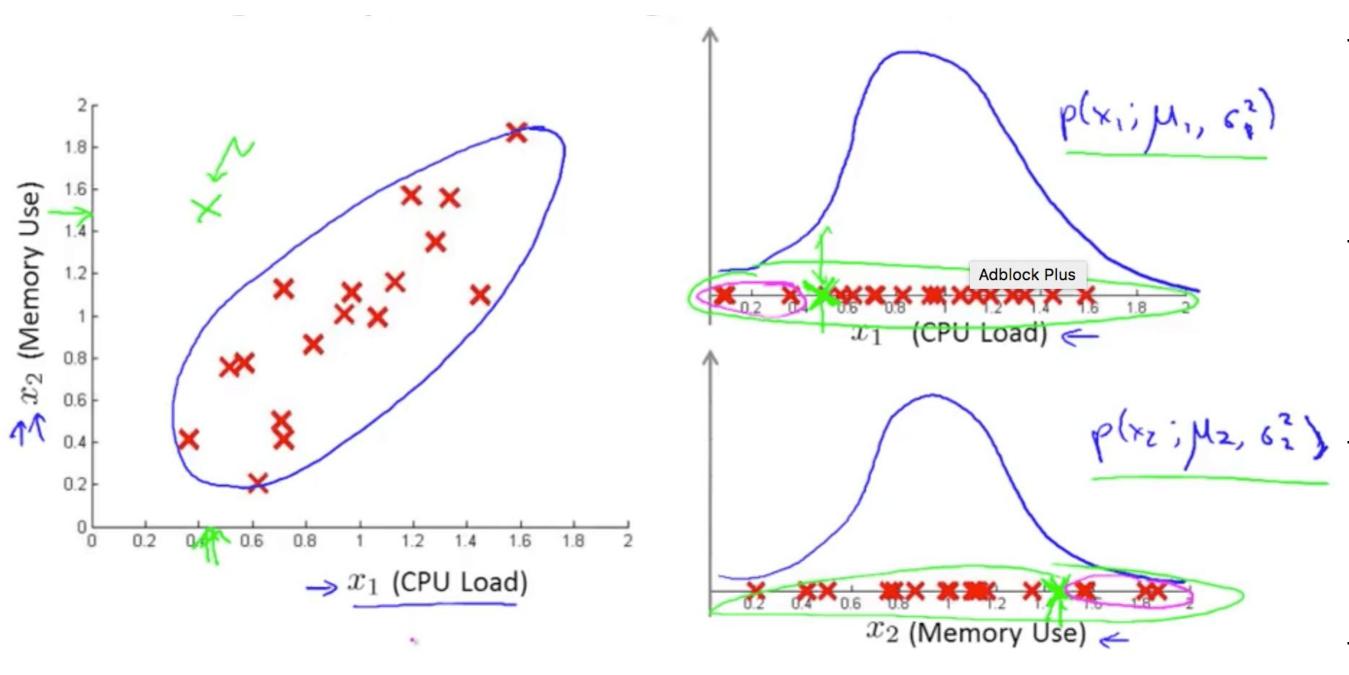
- ...and use clusters! (Cluster Based Oversampling)

source:

<u>SMOTE and ADASYN</u>

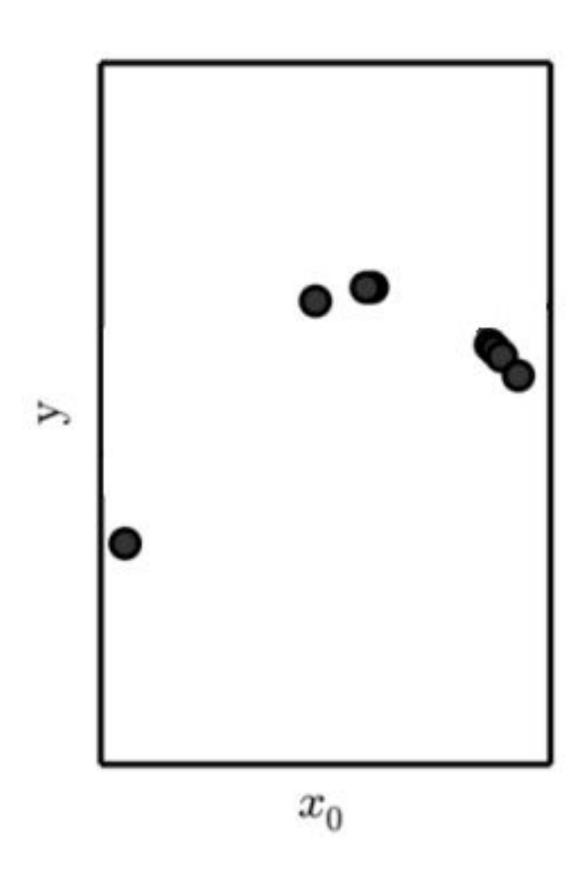
<u>"Clustering and Learning from Imbalanced Data"</u>

SOLUTION 4. - RECAST PROBLEM!

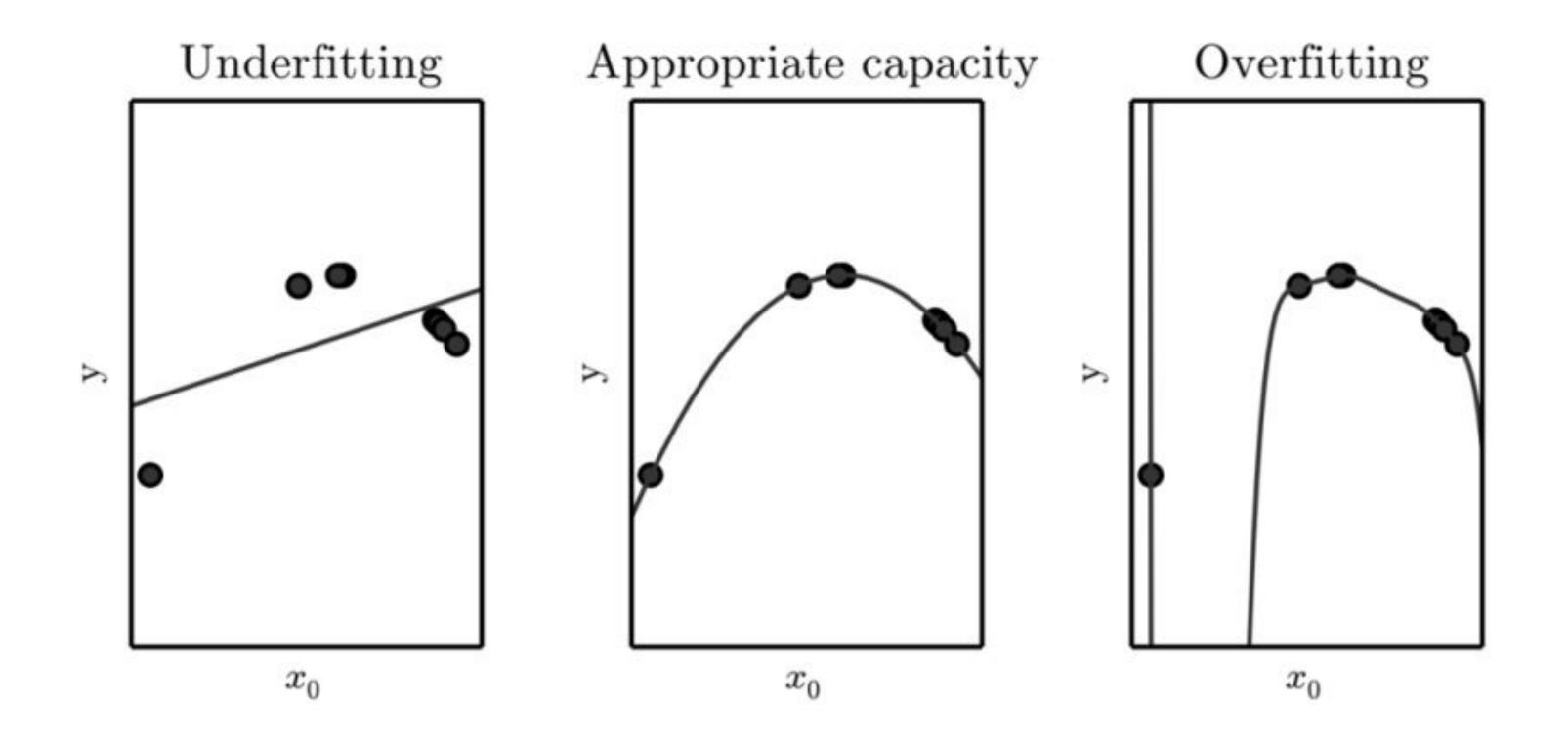


- If the minority class points are so rare, they can be considered "exceptions", or "anomalies"
- There are tools for "one class" classification (eg.: "One class SVM" and "Isolation forests")
- But if we basically get a good **probabilistic model** of the majority class distribution, we are done.
 - This will lead us to "representation learning"

CASE II. - WE DON'T HAVE ENOUGH ANYTHING

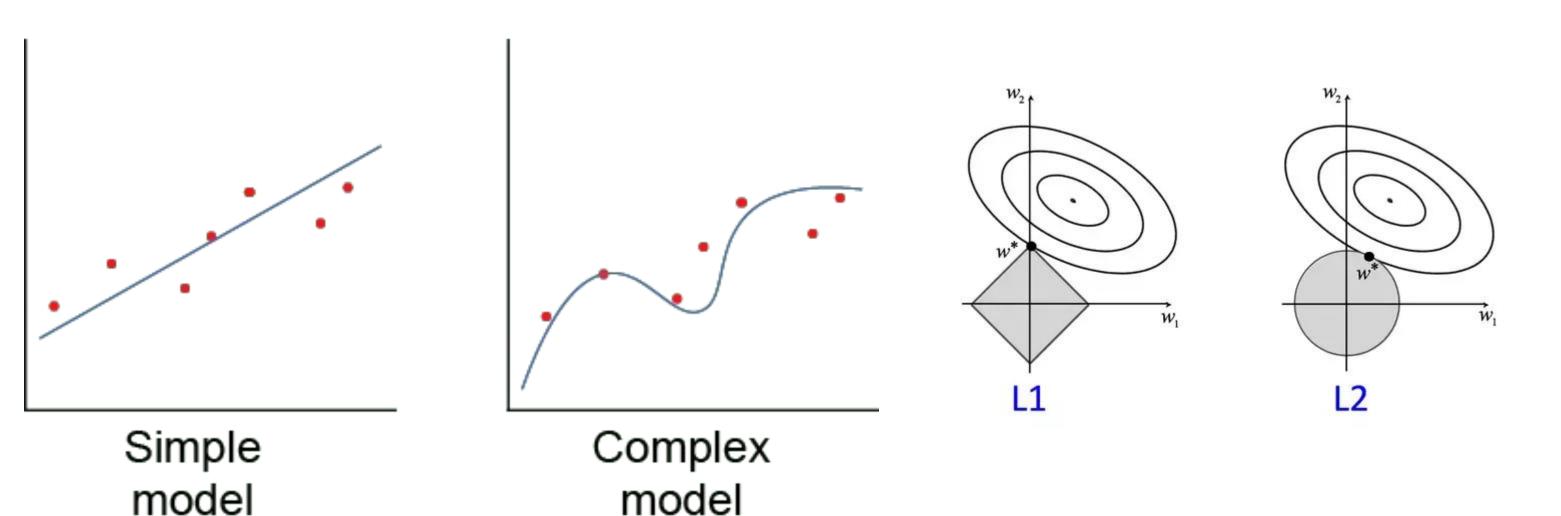


CONNECTION WITH OVERFITTING



source: Overfitting - Wikipedia

FIRST TRY - CLASSIC METHODS FOR STABILITY



Test data Training data Iteration 2 Iteration 3 Iteration k=4 All data

- Modify the model:

- Use a simple model
 - We are often forced to use a complex one since the data itself is complex (dimensions, non-linearity...)
- Use special models (eg. <u>SUFTware</u>)

- Modify the objective:

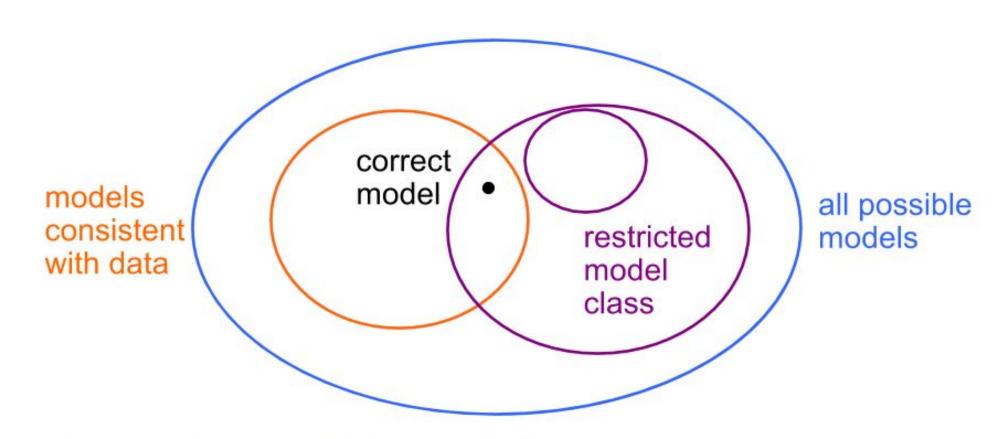
- Add <u>regularization</u> term (Capacity control)
- Use "max margin" objective (like in SVMs)

- Modify the training:

- Use <u>crossvalidation</u> for getting a bit more out of the data
- Use PU Learning

REMARK: ADDING MORE DATA ACTS AS "REGULARIZER"

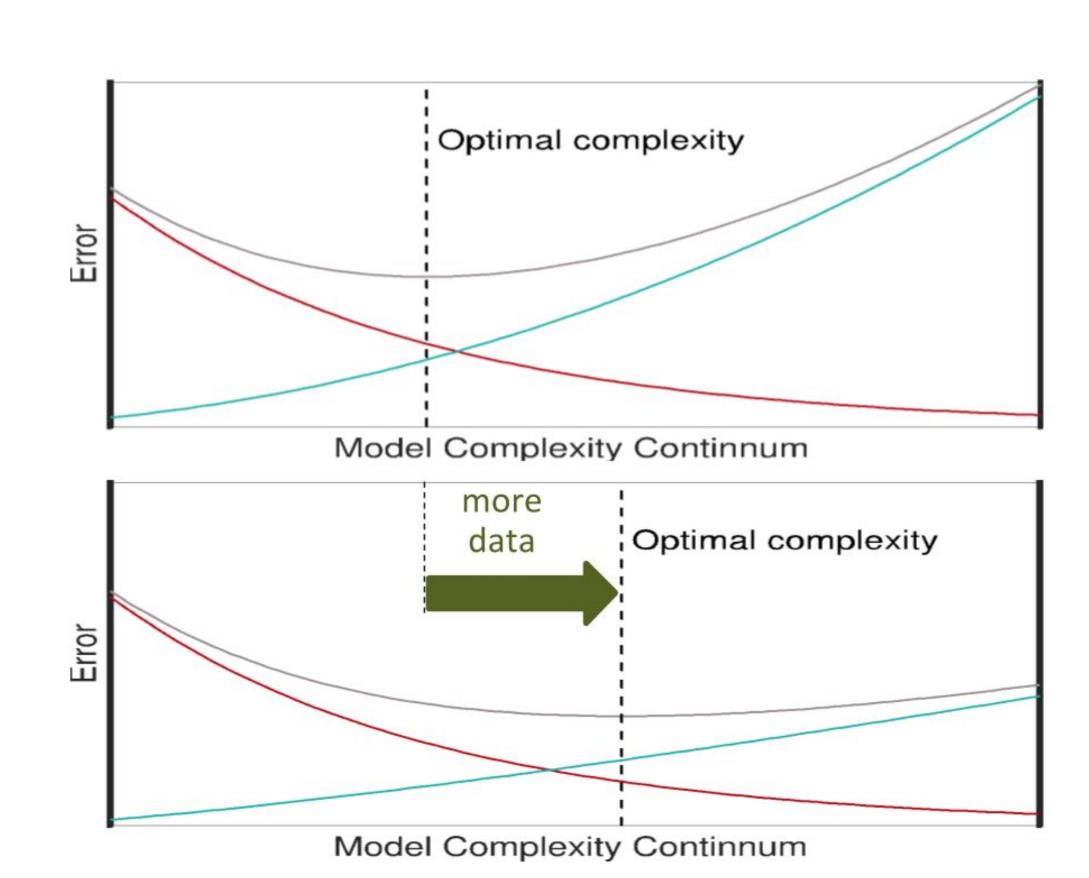
Model Space



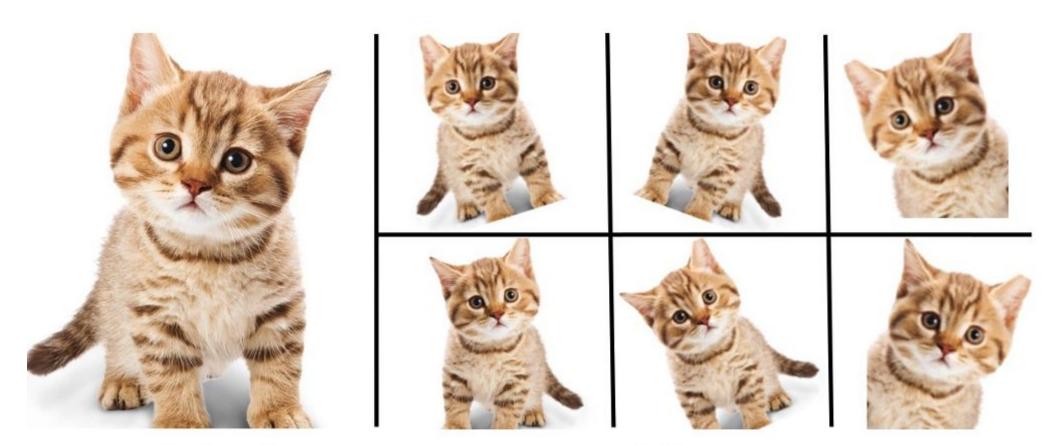
Restricting model class can help

Or it can hurt

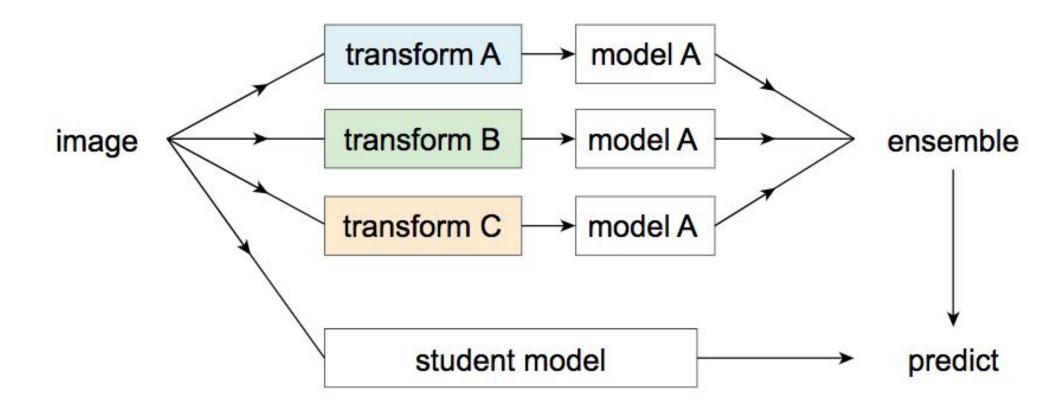
Depends on whether restrictions are domain appropriate



GET MORE "DATA" 1. - GENERATE OR AUGMENT



Enlarge your Dataset



- Data augmentation:

- Use simple operations to modify the data
 - Images: rotate, mirror, crop,...
 - MUST be realistic for the domain distribution

- Data distillation:

- Transform data, train subclassifiers, use them on new data, add predictively labelled data to original.

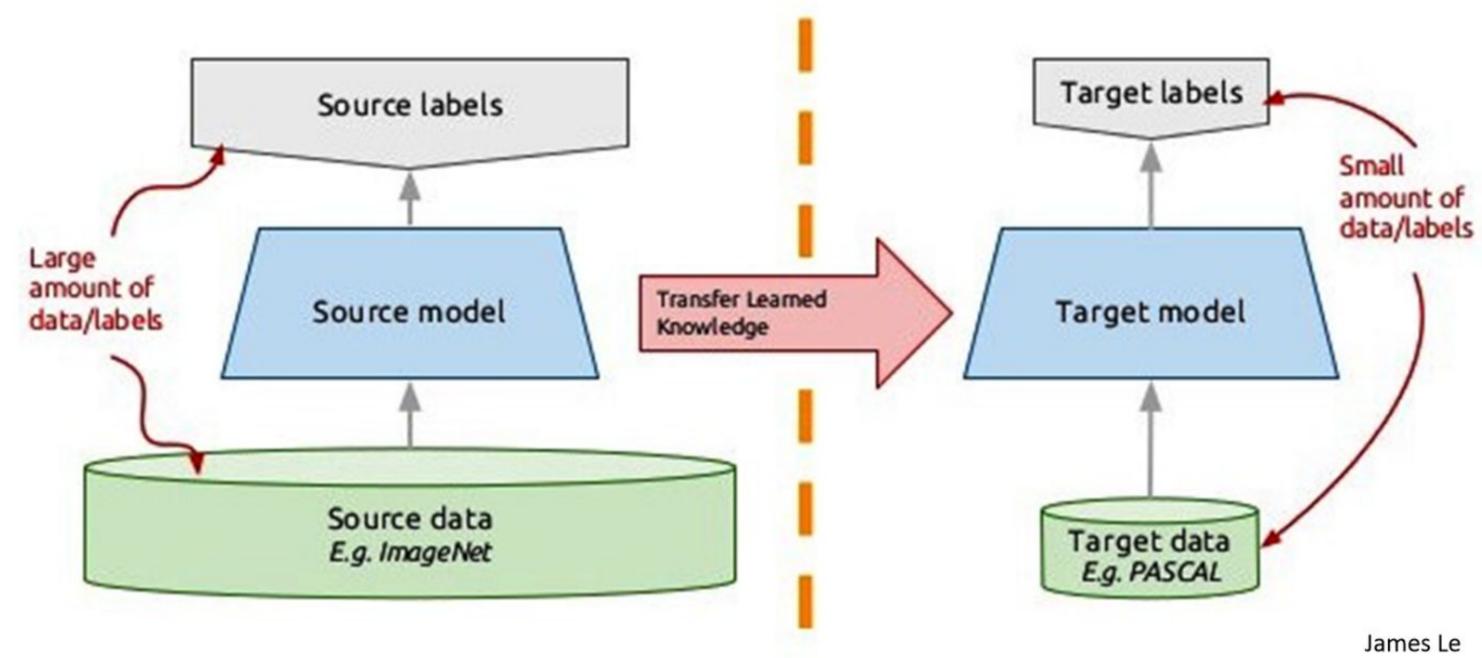
- Weak supervision:

- Can be, that labels wil be noisy - crowdsourcing



GET MORE "DATA" 2. - TRANSFER IT! (COMPRESSED)

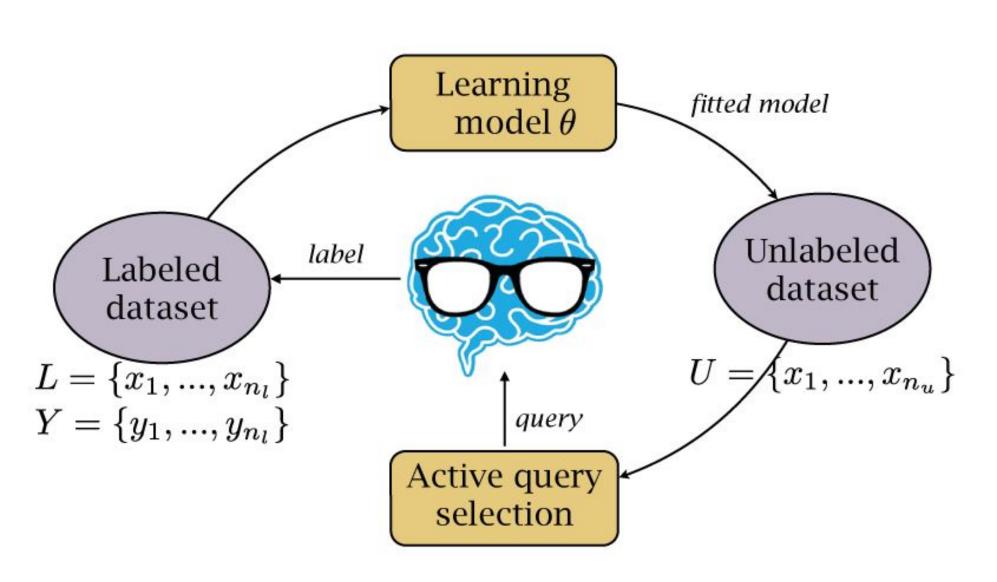
Transfer learning: idea



- Transfer learning!

- A **HUGE** topic in itself (with more and more spohisticated methods for preventing "catastrophic forgetting")
- We have to see, that models are "storing" data, albeit compressed.
- There are plenty of pre-trained models available, USE THEM!
- What model to "transfer"?
 - Notion of "learning a whole representation space" (see eg.: <u>Mixup method</u>)
 - **GANs or VAEs** are generally strong candidates (+ few labeled data case)

GET MORE "DATA" 3. - ASK FOR IT! :-)





- Crowdsource!

- Amazon Mechanical Turk
- or <u>CrowdFlower</u>.

- Design a learning loop!

- Continuous, Online learning
- There are key points worth
 asking for
 (margin, adversarial examples)
 - -> Active learning

source:

<u>"Adversarial sampiing for active learning"</u>

"Atacking machine learning with adversarial examples"

MEASUREMENT VS BUSINESS RISK - THE FALSE FOCUS ON ACCURACY

"I HAVE 90% ACCURACY!"

CLASSIFICATION RISK:

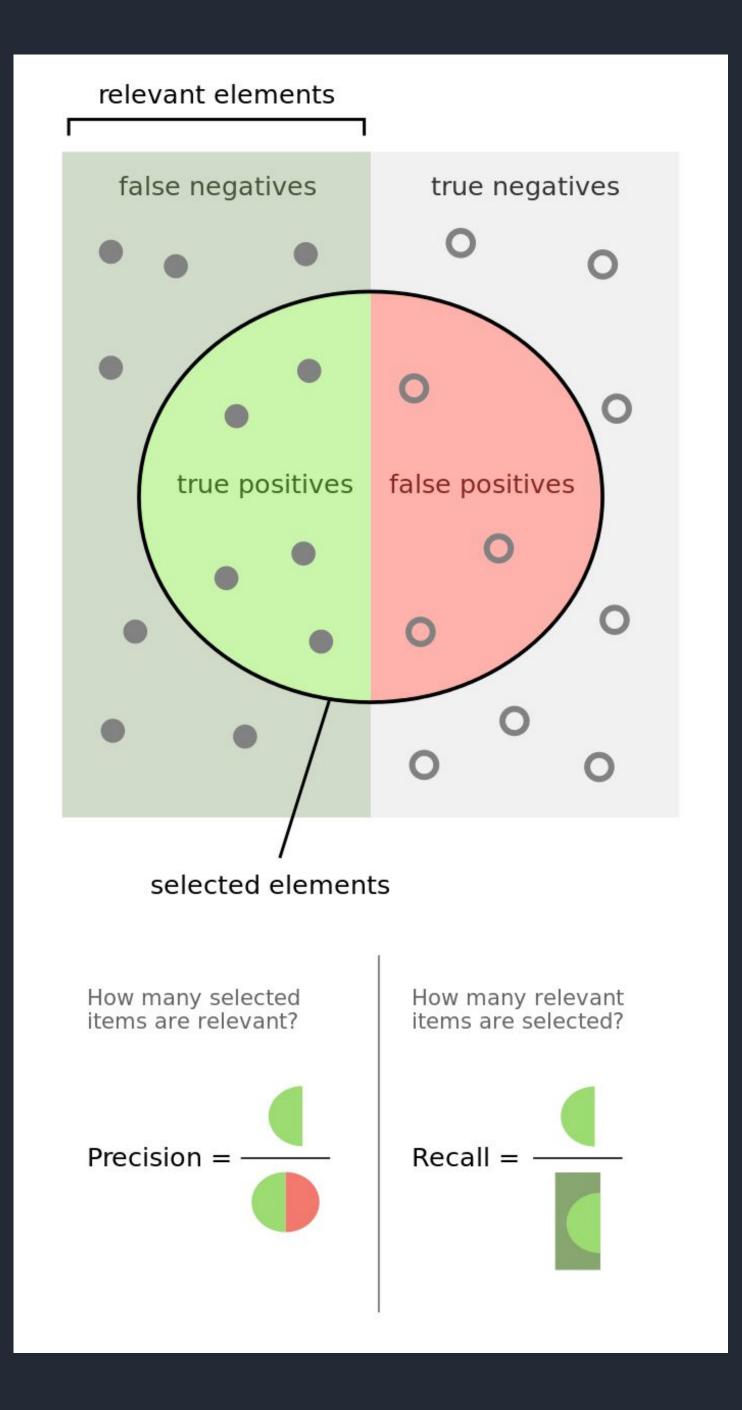
"Your cancer predictions are 90% accurate.

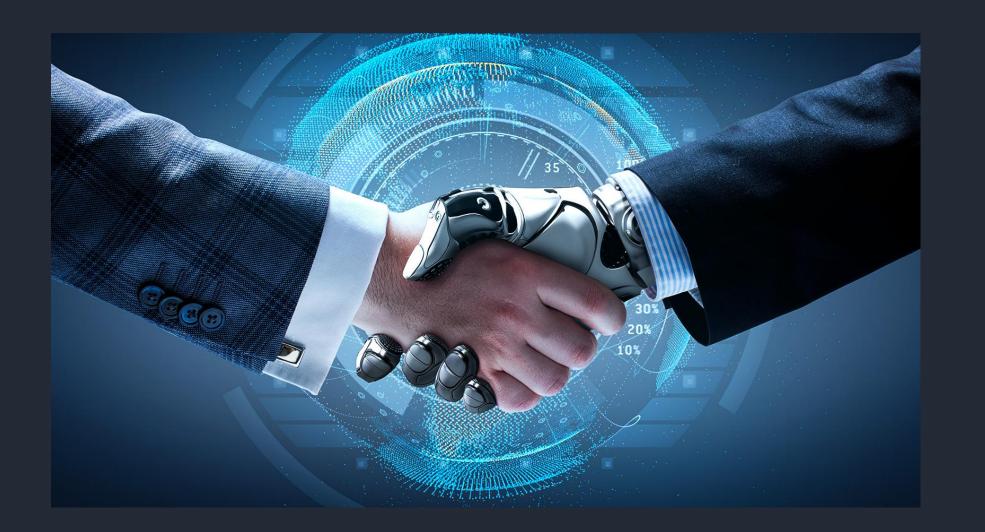
We have 10 dead people."

SOLUTION:

Substitution of huiman expertise is not the way!

Think in cooperative systems!





DON'T REPLACE, AUGMENT!

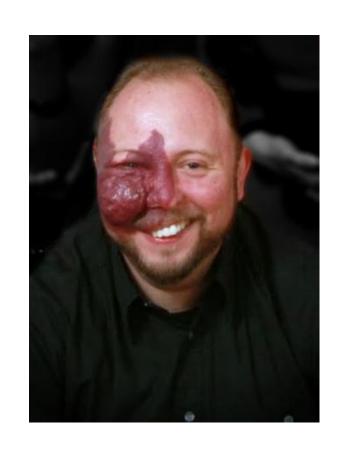
COOPERATIVE SYSTEMS ARE MINIMIZING RISK

Artificial intelligence VS Augmented intelligence

LET'S CONTINUE!







PRESENTATION



COMMUNITY



MYSELF

