# Active learning

Oleksandr Obiednikov

AI Ukraine

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# Agenda

- Motivation
- What is active learning?
- Faster annotation
- Smarter annotation
- Open questions and Tips & Tricks
- Q & A

### Disclaimer

# Likely, everything in this talk did not happen in reality; it's just a figment of my imagination.

Coincidences with real people or events are accidental.

Please don't refer to this talk in press :-)

### Few words about myself



### **Research SDM @ Ring Ukraine**

GitHub: <u>https://github.com/alexobednikov</u> Facebook: <u>https://www.facebook.com/alexander.obednikov</u> e-mail: obednikov.alex@gmail.com

You can talk to me on the following topics:

- Putting AI into production
- CV and Audio analysis
- Metric learning and Re-ID
- Object detection and recognition.
- GANs and domain adaptation
- just chat...

### **Motivation**

### **Models are the bottleneck in Machine Learning Data is the bottleneck in Machine Learning**

### Labeled data is the bottleneck in Machine Learning

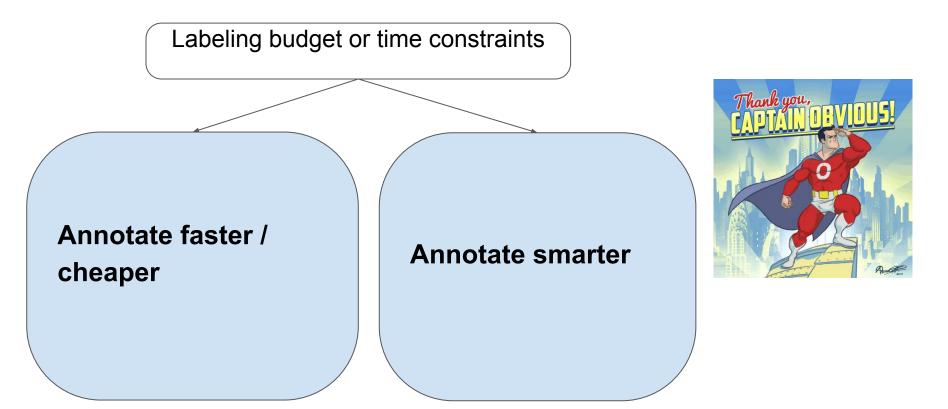
# **Motivation**

### Labeled data is the bottleneck in Machine Learning

#### Why?

- Most of the current "practical" ML is supervised learning
- Getting labeled data either
  - A huge amount of unlabeled data that needs to be annotated
  - Expensive to get even a single labeled example
  - Noisy annotation
  - o ...
- To tackle "long-tail" you need to have a lot of data

# So what to do with it?



# So what to do with it?

Labeling budget or time constraints

#### Annotate faster / cheaper

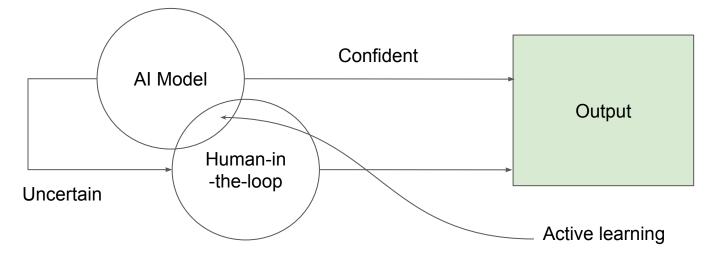
- Annotation UX
- "Machine" assisted annotation (e.g. pre-annotation via ML model, steam-like suggestions, etc)

#### Annotate smarter

 Select the most informative data for annotation



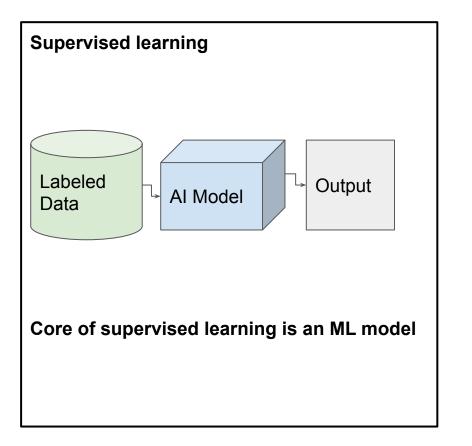
# What does it have to do with active learning?

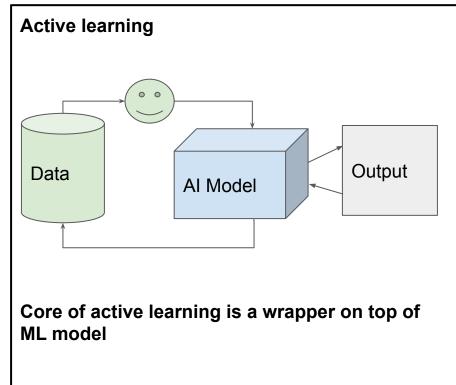


Active learning focuses on ML model / Human interactions. E.g. how to organize cooperation with human for

- 1. getting data
- 2. supporting when a model is not confident
- 3. etc

# Active learning is not a model; it's strategy / protocol





#### "Just add some machine learning in the annotation loop" they said...

Case study: Object detection annotation on a video

#### Data annotation flow:

Data annotator draws bounding boxes on **key frames**  $\rightarrow$  interpolation in between  $\rightarrow$  Bingo!

Case study: Object detection annotation on a video

#### Modified data annotation flow:

Presentation with Huge Object detector  $\rightarrow$  Data annotator corrects bounding boxes if needed on key frames  $\rightarrow$  tracker  $\rightarrow$  interpolation in between  $\rightarrow$  **<your guess>** 

Case study: Object detection annotation on a video

#### Modified data annotation flow:

**Pre-Annotation with Huge Object detector**  $\rightarrow$  Data annotator **corrects** bounding boxes **if needed** on key frames  $\rightarrow$  interpolation in between  $\rightarrow$  **Bingo! no bingo :-(** 

#### Modified data annotation flow iteration 2:

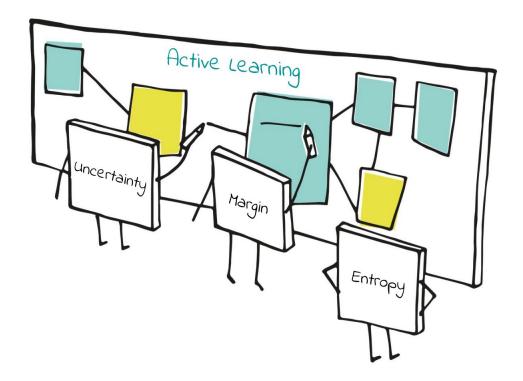
Full replication of Data Annotator pipeline by  $ML \rightarrow Data$  annotator with usual flow  $\rightarrow Bingo!$ 

Case study: Object detection annotation on a video

#### Lessons learned:

- Partial replacement of separate component may be not enough. Likely won't be enough.
- Thinking about annotation UX may be more beneficial than thinking about the final result.
- Data annotation speed and statistics is more about people rather than numbers.

### **Smarter** annotation



$$u(x) = 1 - p_1(x)$$

Uncertainty

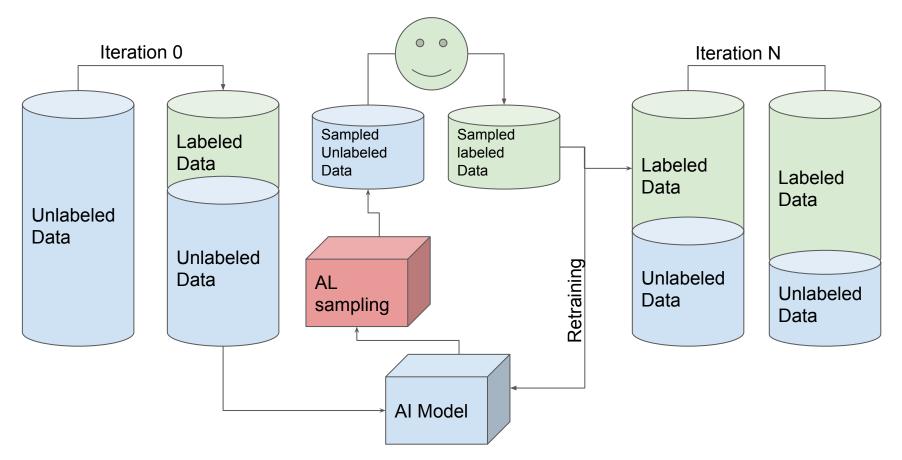
$$m(x) = p_2(x) - p_1(x)$$

$$e(x) = \sum_{i=1}^{K} p_i(x) * \log p_i(x)$$

Entropy

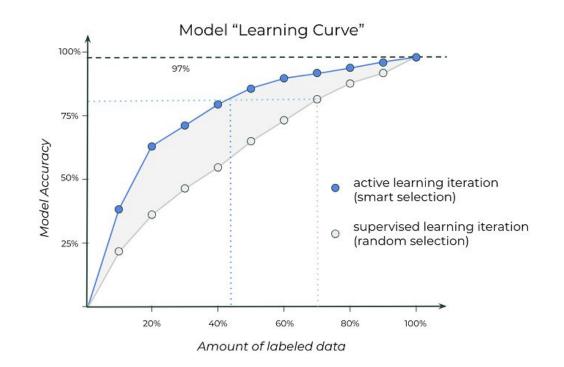
\*https://towardsdatascience.com/learn-faster-with-smarter-data-labeling-15d0272614c4

# Active learning step-by-step



# Smarter annotation. What it gives to me?

- Reasonable result faster
- Better learning curves
- Helps with "long-tail"
- Likely outperform supervised learning



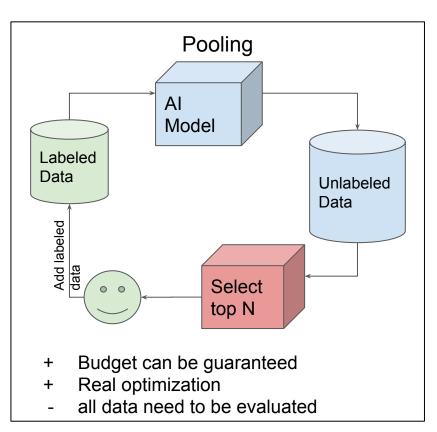
\*https://www.kdnuggets.com/2018/10/introduction-active-learning.html

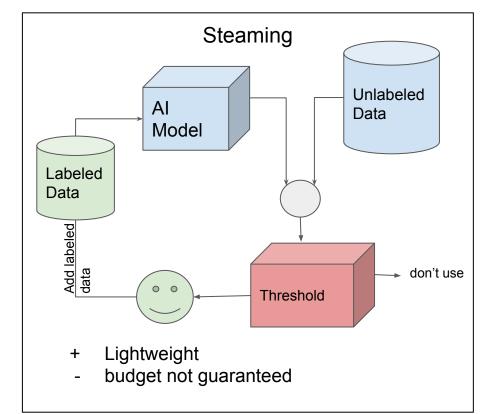
# Some examples of sampling approaches

- Model uncertainty based: criteria(x) = 1 p(x)
- Max class margin based: criteria(x) = p(x | y = dog) p(x | y = cat)
- Entropy based:  $criteria(x) = \sum p(x) * \log p(x)$
- Information density:  $criteria(x) = 1/N * \sum ||f(x) f(xj)||$
- etc

*Captain note:* you cannot just annotate data points that has the largest uncertainty.

# Active learning approaches





# What can we tune? What are hyperparameters?

- Pooling, streaming or custom protocol?
- Sampling strategies
- Pool size for pooling and threshold for streaming
- When we want to stop

# Problems and open questions

- Bias and fairness
- Easy to understand, hard to implement
- In real scenarios active learning pipelines often sometimes collapses to
  - finding incorrect labeled data
  - finding corner cases where even a human is highly unconfident

## References

- https://www.kdnuggets.com/2018/10/introduction-active-learning.html
- <u>https://towardsdatascience.com/learn-faster-with-smarter-data-labeling-15d02</u>
  <u>72614c4</u>
- <u>https://arxiv.org/abs/1801.05124</u>
- http://parnec.nuaa.edu.cn/huangsj/alipy/
- https://www.youtube.com/watch?v=V33Ut36eUsY

### Questions

### We are hiring

https://grnh.se/a93b70881