# Part 1 - How to Start and Common Issues

## Training Deep Networks from Zero to Hero: avoiding pitfalls and going beyond

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SIBGRAPI 2021

# Agenda

How to Start

Common Issues

# 1 - Data quality

## Basic principles

- Defined consistently with regards to the problem
- Cover all important cases
- Dataset size is appropriate

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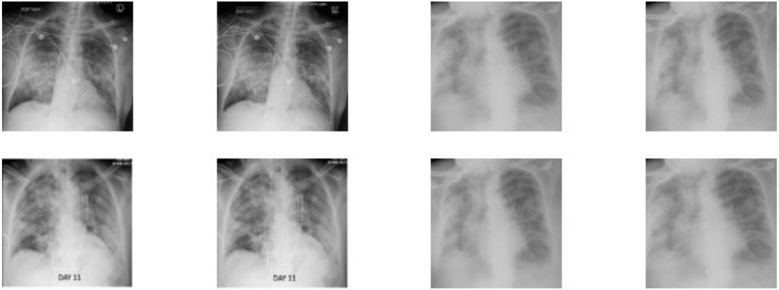
## Problems to look for (even in benchmark datasets)

- Wrong labels
- Noise and outliers
- Duplicated instances


DAY 11
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The ending made my heart jump up into my throat. I proceeded to leave the movie theater a little jittery. The movie was better than I expected. I don't know why it didn't last very long in the theaters or make as much money as anticipated. Definitely would recommend.

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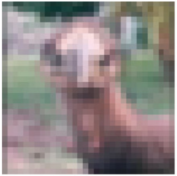
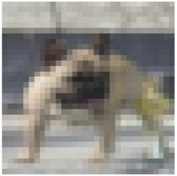
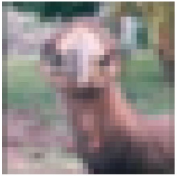
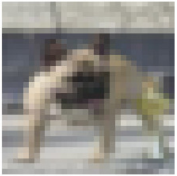
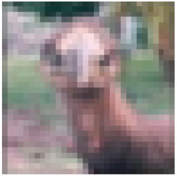
Label: Negative



bird





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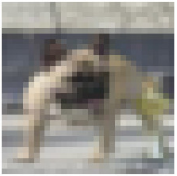

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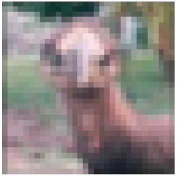

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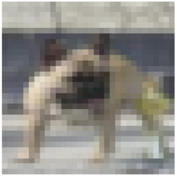

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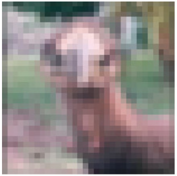
automobile



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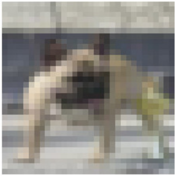

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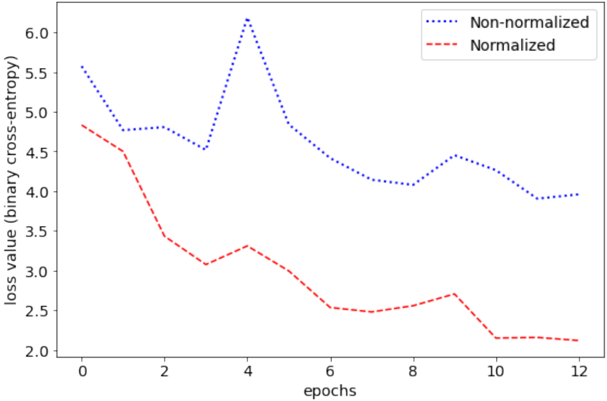
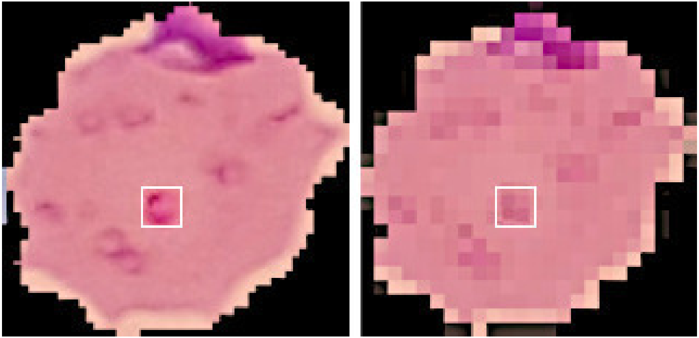
# 2 - Normalization

DNNs do not work well with arbitrary ranges.

- 0-1 MinMax Scaling
- z-Score Standardization



After (or despite) pre-processing, the patterns required for learning the concept are present



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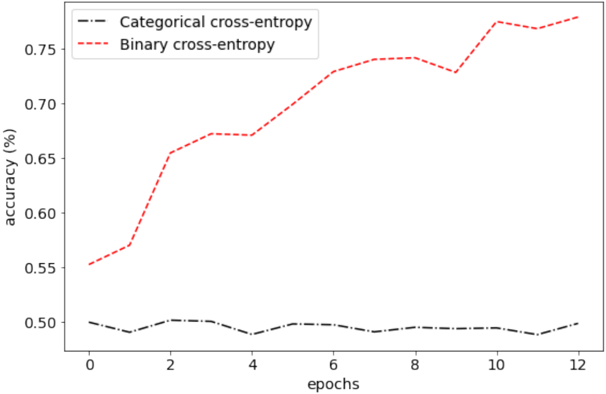
## Tasks

- Binary classification
- Multi-class classification
- Regression
- Detection
- String matching
- Recommendation




...for a 2-class problem

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- Mean squared error (MSE)
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### Cosine Distance

cosine of the angle between two vectors

Know your loss values

Example: 5 class problem

### Categorical cross-entropy $-\sum y_i \ln(\hat{y}_i + 10^{-6})$

- All classes equally probable: $-1 \cdot \ln(1/5) = 1.60$
- Correct class with probability zero (and all other equally probable): 13.8

### MSE $\sum(y_i - \hat{y}_i)^2$

- All classes equally probable: 0.80
- Correct class with probability zero (and all other equally probable): 1.25

# 5 - Model Tuning and Validation

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**WRONG**. Why?

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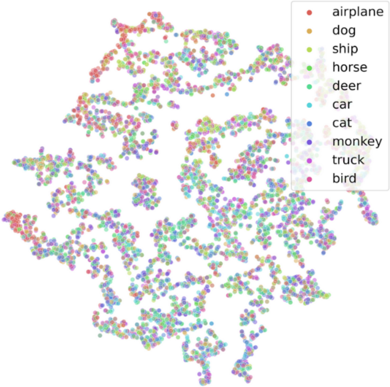
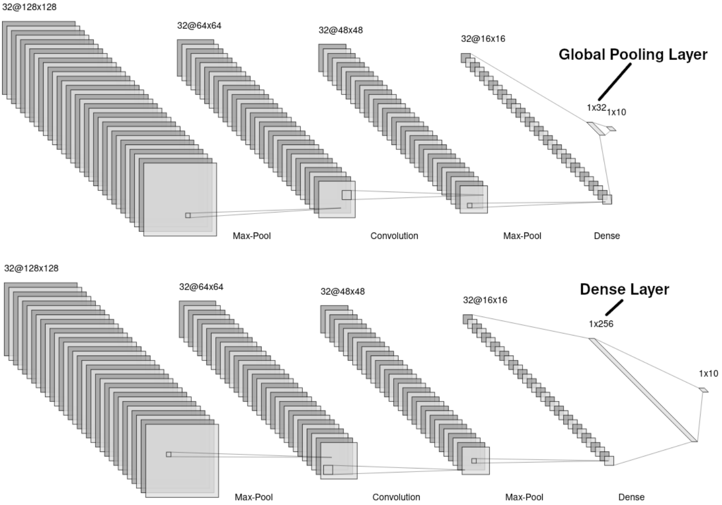


Usually we visualize the output of the layer prior to prediction



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For sensitive data, it is important to have also **external validation**: use the model to evaluate on data acquire in other contexts

- in medical data this is crucial

# Summary

- PROBAST: A Tool to Assess the Risk of Bias and Applicability of Prediction Model Studies
  https://www.acpjournals.org/doi/10.7326/M18-1376
  - participants, predictors, outcome, and analysis
- CLAIM: Checklist for Artificial Intelligence in Medical Imaging
  https://pubs.rsna.org/doi/10.1148/ryai.2020200029
  - study design, data, ground truth, evaluation, discussion

1. Data quality
2. Normalization
3. Input Representation
4. Loss Function and Evaluation Metrics
5. Model Tuning and Validation
6. Visualization
7. Internal vs External Validation

# Agenda

How to Start

Common Issues

## Small Datasets

- Regression: usually easier, require cover all output interval
- Classification: 1000-1500 instances per class to allow learning

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## Alternatives

- Very small dataset ($n < 1000$): feature extraction using pre-trained networks and use of external classifier
- Small datasets ($1000 \leq n \leq 5000$): data augmentation and/or transfer learning

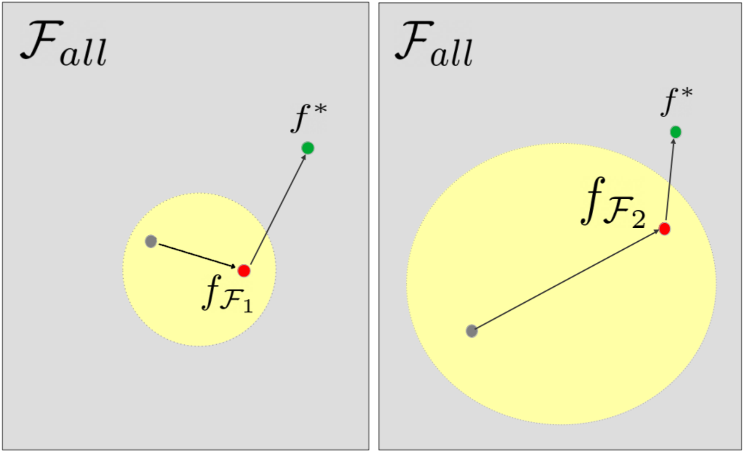
# Imbalanced data

In this case be careful to use:

- metrics that take into account the unbalanced scenario
- make sure the distribution of future data will have similar distribution, or update the model if not
- instance weights by class so that the minority classes has more weight during training
- use data augmentation to mitigate the issue

# Model complexity and generalization

The Bias-Variance dilemma and Deep Neural Nets



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- Prefer lower capacity models if possible
- Give more importance to the data quality
- Evaluate rigorously

# Models under attack

Training set without attack

CAR (56%)
AIRPLANE (30%)
HORSE (7%)

Pixel attack: if a malicious person has access to the training set...

**Training set with pixel attack**

CAR (56%)
AIRPLANE (30%)
HORSE (7%)

AIRPLANE (61%)
CAR (31%)
HORSE (6%)

# Bibliography I

Moacir A. Ponti, Fernando dos Santos, Leo Ribeiro, Gabriel Cavallari. **Training Deep Networks from Zero to Hero: avoiding pitfalls and going beyond**.
SIBGRAPI, 2021. Tutorial.
https://arxiv.org/abs/2109.02752

Moacir A. Ponti, Leo Ribeiro, Tiago Nazaré, Tu Bui, John Collomosse. **Everything You Wanted to Know About Deep Learning for Computer Vision but were Afraid to Ask**.
SIBGRAPI-T, 2017. Tutorial.

# Bibliography II

Moacir A. Ponti, **Introduction to Deep Learning** (Code).
Github Repository:
https://github.com/maponti/deeplearning_intro_datascience
CNN notebook: https://colab.research.google.com/drive/1EnNjtzdw8ftIO7I9xCUhb-ovq1iNy4pf