PROGRAMMING IN PYTHON II

Project Design and Outline



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MOTIVATION



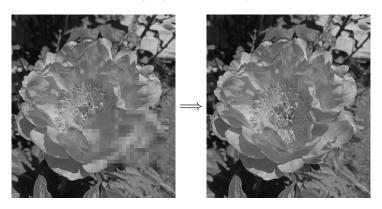
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- Spoiler alert: The choice of the ML method itself is only one aspect of many

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- We will use our ML project as example



OVERVIEW



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 - 5. How to evaluate the methods/models?
- There is no one-fits-all solution! Specific tasks require specific considerations!

PROJECT GOAL



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- Rinse and repeat to overcome language barriers

DATA



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 - Best case but rather rare (our hunger for data is only limited by computational restrictions!)
- Sometimes the goals will follow from existing but insufficiently large data
 - Common case
 - Has influence on choice of ML method
 - ☐ Allows for educated guesses at sufficiently large data size
 - ☐ Can be a starting point for collecting more data

Data (2)

Sometimes the goals are not backed up by any data
 Very tricky and potentially dangerous!
 You would have to make guesses about how much and which data would be needed
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 - Perform data preprocessing and augmentation
 - Normalization, oversampling, cross-validation splits, data augmentation, . . .

HARDWARE/SOFTWARE



What hardware/software do you have? What hardware/software could you have?

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- Size of RAM and disk storage?
- Hardware compatible with ML software? Software restrictions from company/collaborations?
- Short-term or long-term project?
 - Rent or own? Little compute over long time or lots of compute over short term?
 - Possible start: First design/implement/experiment on owned hardware, then perform final tuning on rented hardware if needed

ML METHODS



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 - Literature research
 - □ Later semesters of AI study
- Start with baselines/less complex methods and models
 - Statistics, logistic regression, SVM, Random Forest, . . .
 - Check Supervised Learning before Reinforcement Learning and Unsupervised Learning

EVALUATION



How to evaluate the methods/models?

■ Which score/performance measure?

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- Do you need to correct for biases?

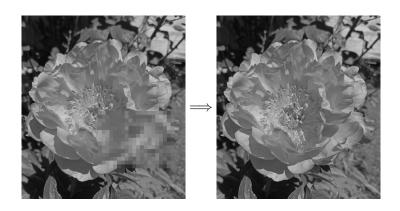
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- Do you need to correct for biases?
- Which aspects of the goal are more important?
- What do you want to generalize to?

PYTHON II PROJECT



Python II Project: Goal (1)



Python II Project: Goal (2)

- Image Depixelation (recreation of pixelated area within an image)
- End goal: Best score on challenge server leaderboard
 - □ Pixelated image is fed into model, and model predicts plausible values for the pixelated area
 - Size of the pixelated area and pixelation block size should be freely selectable
 - ☐ Images should be grayscale images

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 - Pixelated image is fed into model, and model predicts plausible values for the pixelated area
 - Size of the pixelated area and pixelation block size should be freely selectable
 - Images should be grayscale images
- What is "plausible"?
 - Luckily, the challenge server decides for us: "Plausibility" is measured by the root-mean-squared error (RMSE) of the predicted pixels

Python II Project: Data (1)

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- We will have the following data:
 - ☐ JPEG images up to 250kB
 - 100 images per student
 - ☐ Assumption: We collect roughly 30k valid images

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We will crop out parts of the original images, so we know the ground truth (no need to collect labels)

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- This is probably a case with sufficient data for training our methods, but
 - ☐ We can use data augmentation to increase the dataset size
 - We could use additional data from the Internet (but it will not be necessary)
- We will have to
 - Clean up the raw data (exclude invalid files)
 - Perform analysis and preprocessing
 - □ (Possibly) perform data augmentation

Python II Project: Hardware, Software and Methods

Hardware:

- Notebook with CPU and 4GB of RAM should suffice
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 - \Box Python \geq 3.9
 - PyTorch

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Hardware: ☐ Notebook with CPU and 4GB of RAM should suffice ☐ No need to rent/buy expensive hardware to speed up computations (you can, if you want)
Main software: □ Python ≥ 3.9 □ PyTorch
Methods: ☐ Simple Convolutional Neural Network (CNN) ☐ You may also use other NN types/more complex setting: ☐ Design and fine-tuning is up to you

Python II Project: Evaluation

- Challenge server score determines the evaluation method
- Will use the root-mean-squared error (RMSE) of the predicted pixels