

MACHINE LEARNING FOR HUMAN DATA – FINAL EXAMINATION

Instructor

Michele Rossi - michele.rossi@unipd.it

Lab. classes

Francesca Meneghello - francesca.meneghello.1@unipd.it

Eleonora Cicciarella - eleonora.cicciarella@phd.unipd.it









Università degli Studi di Padova

General guidelines

The final exam is project-based

- This does not mean that you can avoid understanding the theory...see the next slides
- 1. Pick a project among the 11 options that we provide to you: each consists of a challenge and an associated dataset
- Design one/more original solution(s) to the problem based on neural networks, implement it/them in TensorFlow and evaluate and compare the performance
- 3. Prepare a report and a presentation describing your work
- You can work in a group with another student
 - max 2 people per group
 - you are free to arrange the groups
 - both members have to contribute to the work

Exam dates and submission deadlines

- Exam: January 28-29, 2025
 - report+code submission deadline: Jan. 25, 2025
- Exam: February 18-19, 2025
 - report+code submission deadline: Feb. 15, 2025
- Exam: June 18-19, 2025
 - report+code submission deadline: June 15, 2025
- Exam: July 2-3, 2025
 - report+code submission deadline: June 29, 2025
- Exam: September 18-19, 2025
 - report+code submission deadline: Setp. 15, 2025

Exam dates: important notes

- The exam will be held in presence
 - online exams are no longer allowed by UNIPD
- Depending on the number of students we may need to split you into groups that will take the exam on different days
 - the exam dates in the previous slide indicate the first days of the session
 - please, be prepared to be scheduled for a different day than the one indicated (try to be available for the day of the exam and the following ones; in case you have unmovable appointments, inform us as soon as you enroll)
 - we will send you the schedule some days before the exam when the UNIWEB enrollment will close

For the final examination you must



Fill out the group selection form in Moodle indicating the students (1 or 2) in your group (we will send the instructions through the Moodle's news channel) → remember to do that!



Upload in Moodle (following the instructions about naming etc.)



- A. a report (use the LaTex template available on Moodle)
- B. the code of the implementation in **TensorFlow**
- 3. Prepare a presentation through slides (20 minutes strict, possibly including a demo) for the day of the exam

The report

- Should be done in LaTex following the template available on Moodle
- 2. Should be written in a clear and organized manner
- 3. Should include graphical presentations of your approaches
- 4. Should clearly show and discuss the results



FILE

Project report - Latex template

"We Rock the Hizzle and Stuff" hints on how to write a nice research essay

Michele Rossi[†], Author two[‡]

Group self-selection in Moodle

Deadline: when you enroll in UNIWEB for the exam You can fill it out also before (recommended)

2024-SC2738-003PD-2024-SCQ4106915-N0-SC2738 / Group and project self-selection



GROUP SELF-SELECTION

Group and project self-selection

Group self-selection

Settings

Groups

More ~

Opens: Wednesday, 30 October 2024, 4:30 PM

Please, create a new group by yourself or with one of your colleagues (i.e., max 2 people per group).

As the group name, use SurnameA (e.g., Rossi) or SurnameA_SurnameB (e.g., Meneghello_Cicciarella) depending on whether you are alone or with a colleague.

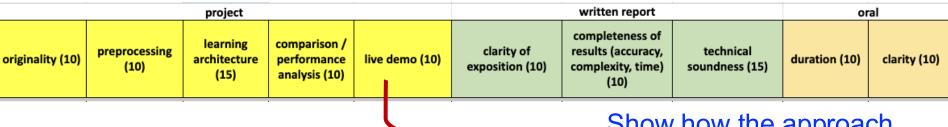
As the group description, indicate the ID of the project you selected (A1, A2, A3, B1, B2, C1, C2, C3, C4, D1, D2, D3).

Set a **password** for the group and share it with your colleague to enable them to become part of the group (not needed if you are alone).

Available projects

Evaluation

- The evaluation will consider different aspects
 - about the report, the presentation and the project itself



- Your grade will be computed by:
 - 1. Summig the points (max 110)
 - 2. Multiplying the sum by 0.424242
 - 3. Subtracting 11.69
 - 4. Limiting the score in [0, 32]

see the details in the LaTex template for the final report (on Moodle)

Show how the approach works on some examples (using pre-trained networks) or a walkthrough

Guidelines

- Prepare the project and the report considering the grid we use for the evaluation (see previous slide)
 - pay attention to the pre-processing phase (normalize the data)
 - create original neural network architectures
 - compare the performance of different approaches (use the correct metrics...check about data balancing)
 - evaluate the performance of the algorithms in terms of running time and complexity (memory occupation)

Guidelines

Be creative!

- We provided you with some ideas for possible project developments, but original works are always welcome!
- You can use the neural network architectures seen during the labs and/or experiment with new approaches!
- We provide you with some references but try to explore a bit other contributions in the literature that may be helpful (search for them in https://scholar.google.it/)
- Pre-processing techniques may be useful
- Implement your own neural network architecture...DO NOT use pre-trained models from Keras: the objective of the project is that you put into practice the things you learned during the theoretical lessons, not to improve your skills about reusing networks/code developed by others:)

Guidelines

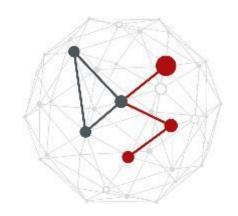
- The use of TensorFlow is mandatory
 - Pytorch is only allowed for spiking neural networks through snntorch
- The use of pretrained networks is not allowed
 - You can use them for comparison but cannot be the main architectures
- During the exam we will ask you the reasoning behind using the specific architectures (e.g., CNN/RNN/attention...)
 - Do not use the NN functions as black boxes: you need to understand why you are using the specific architectures
 - REMEMBER: Python is not intelligent, it takes something as input and provides an output, it only checks the shape of the data → pay attention and use your theoretical knowledge

Common mistakes to avoid

- Data not correctly normalized
 - This is an important step for ML algorithms to not have biases in the algorithm
- Preprocessing not considered
 - In addition to ML you may need to apply some signal processing algorithms to clean the data before NN
- Train/validation/test sets not correctly split
 - The three sets do not have to overlap: no data from training should be used during validation or test
- Validation performed on a small number of samples that is not statistically significant
 - e.g., evaluation performed on 1 or 2 samples...
- Complexity of the algorithms in terms of time and memory not analyzed
- Use wrong input data
 - e.g., for IMU datasets, obtain the activity prediction by using single IMU measurements and not a sequence of measurements



PART B AUDIO SIGNALS











Proposed Projects

PART A - ON BODY AND ENVIRONMENTAL SENSORS

- 1) A1: Activity recognition with four accelerometers
- 2) A2: Pathological gait recognition
- 3) A3: Motor imagery classification from EEG for brain computer interface

PART B - AUDIO SIGNALS

- 1) B1: Speech command recognition (keyword spotting)
- 2) B2: Environmental sound classification

PART C - IMAGES

- 1) C1: Sleep posture monitoring
- 2) C2: Bone age prediction from hand radiographs
- 3) C3: Lung disease prediction from X-ray images
- 4) C4: Blood cell type prediction

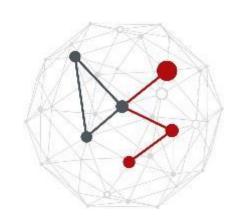
PART D - RADIO SIGNALS

- 1) D1: Activity recognition through Wi-Fi devices
- 2) D2: Gesture recognition through radars





PROJECT B1











Università degli Studi di Padova

Project B1 "Speech recognition"

Reference papers

[Sainath15] Tara N. Sainath, Carolina Parada, Convolutional Neural Networks for Small-footprint Keyword Spotting, INTERSPEECH, Dresden, Germany, September 2015.

[Warden18] Pete Warden, Speech Commands: A Dataset for Limited-Vocabulary Speech Recognition, arXiv:1804.03209, April 2018. https://arxiv.org/abs/1804.03209

- The authors are from Google Inc.
- Reference dataset released by Google [Warden18]

Dataset description

- Reference dataset for small-footprint keyword spotting (KWS)
 - Released in August 2017
 - 65,000 one-second-long utterances of 30 words
 - by thousands of different people
 - released under creative commons 4.0 license
 - collected by AIY (https://aiyprojects.withgoogle.com/)

Google blog

https://ai.googleblog.com/2017/08/launching-speech-commands-dataset.html

Speech dataset (2.11 GB uncompressed)

http://download.tensorflow.org/data/speech_commands_v0.02.tar.gz

Approaches for implementing a KWS engine

- LVCSR based KWS This approach uses a two-stage process. In the
 first stage, the transcription of the speech into words is done using a
 Large Vocabulary Continuous Speech Recognition (LVCSR) engine,
 outputting formatted text. In the second stage, a textual search for the
 key-words within the text is performed. Using this approach, results
 from LVCSR and the text search are combined to spot the key-words
- Phoneme Recognition based KWS This approach also uses a twostage process. In the first stage, the speech is transformed to a sequence of phonemes. In the second stage, the application searches for phonetically transcribed key-words in the phoneme sequence obtained from the first stage
- Word Recognition based KWS [Sainath15] This approach searches for the key-words in a one stage operation. The recognition is phoneme-based and the KWS engine looks for the keyword in the speech stream based on a target sequence of phonemes representing the key-word

CNN model from [Sainath15]

- Features are obtained from raw audio data
- 40-dimensional log Mel filterbanks coefficients
 - audio frame length 25 ms
 - with a 10 ms time shift
- At every new audio frame
 - Feature vector is obtained
 - And stacked with 23 frames to the left and 8 to the right (32 frames total)
 - This returns 32 frames at a time, spanning over 31 x 10 ms + 25 ms = 0.335 s
- A Convolutional Neural Network (CNN) is used to detect words
- Input to the CNN is a matrix of size t x n = 32 x 40 = 1,280 elements
 - t represents the number of elements in time (number of audio frames)
 - n represents the number of elements in the frequency domain (Mel features)

CNN model from [Sainath15]

- 27-44% improvement for KWS with respect to traditional neural networks
- The paper focus is on
 - Devising CNN architectures with small memory footprint
 - Playing with CNN parameters (number of kernels, strides, pooling, etc.)

Possible project developments

- Experiment with different audio features
 - Type of coefficients (e.g., discrete Wavelet transform)
 - Design of Mel filterbanks
- Play with a standard/deep CNN using
 - dropout, regularization
- Investigate recent/new ANN architectures
 - Autoencoder-based (CNN/RNN autoencoder + following SVM)
 - Attention mechanism and/or inception-based CNN networks
 - Comparison of different architectures: memory vs accuracy

Useful resources

Recent developments

[Chorowski 15] J. K. Chorowski, D. Bahdanau, D. Serdyuk, K. Cho, Y. Bengio, Attention-Based Models for Speech Recognition, Conference on Neural Information and Processing Systems (NIPS), Montréal, Canada, 2015.

[Tang18] R. Tang and J. Lin, Deep residual learning for small-footprint keyword spotting, in IEEE ICASSP, Calgary, Alberta, Canada, 2018.

[Andrade18] D. C. de Andrade, S. Leo, M. L. D. S. Viana, and C. Bernkopf, A neural attention model for speech command recognition, arXiv:1808.08929, 2018. https://arxiv.org/pdf/1808.08929.pdf

White Paper: "Key-Word Spotting - The Base Technology for Speech Analytics" https://pdfs.semanticscholar.org/e736/bc0a0cf1f2d867283343faf63211aef8a10c.pdf

Example code:

https://github.com/tensorflow/tensorflow/tree/master/tensorflow/examples/speech commands/



MACHINE LEARNING FOR HUMAN DATA – FINAL EXAMINATION

Instructor

Michele Rossi - michele.rossi@unipd.it

Lab. classes

Francesca Meneghello - francesca.meneghello.1@unipd.it

Eleonora Cicciarella - eleonora.cicciarella@phd.unipd.it









Università degli Studi di Padova