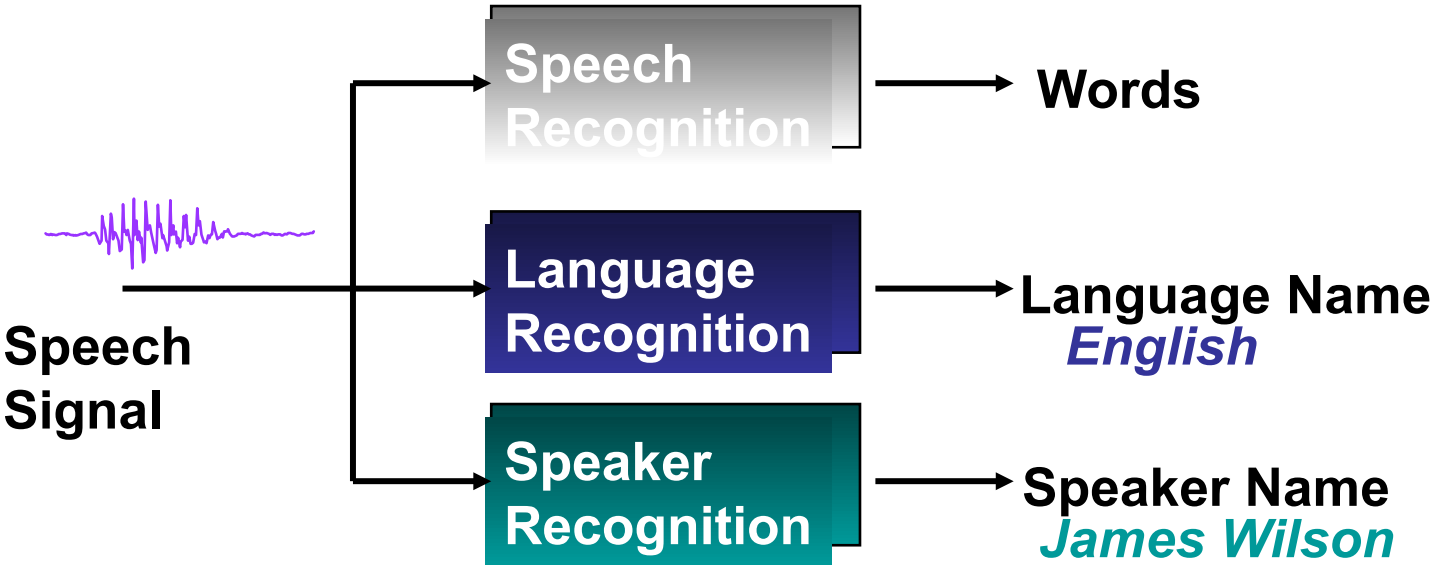
# Natural Language and Speech Processing

Lecture 13: Speaker and Language Recognition. Some General Tips & Tricks.

# Extracting information from speech



# Speaker recognition applications

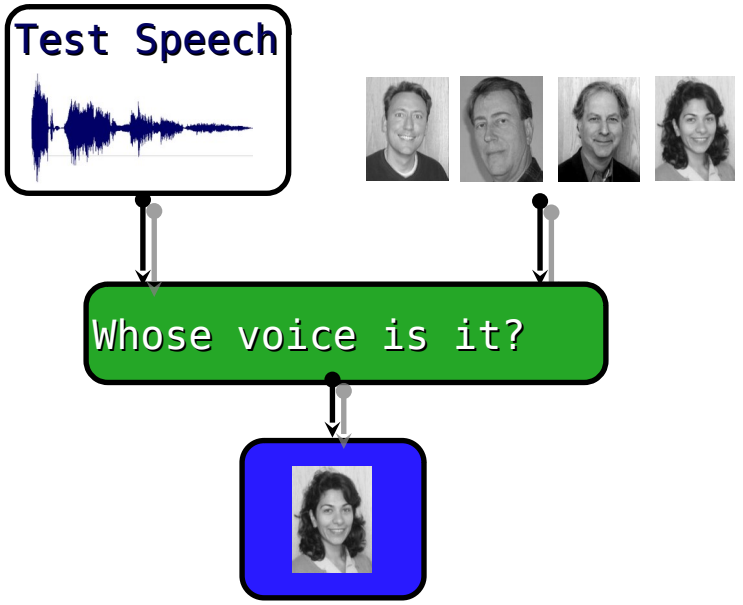
- **Access control**
  - Physical facilities
  - Data and data networks
- **Transaction authentication**
  - Telephone credit card purchases
  - Bank wire transfers
  - Fraud detection
- **Monitoring**
  - Remote time and attendance logging
  - Home parole verification
- **Information retrieval**
  - Customer information for call centers
  - Audio indexing (lectures, podcasts, radio)
  - Personalization
- **Forensics**
  - Voice sample matching

# Tasks

- Speaker identification
  - Closed set and open set
- Speaker verification
- Also:
  - Speaker change detection
  - Speaker diarization (clustering of speaker segments according to speaker)
  - Speaker overlap detection

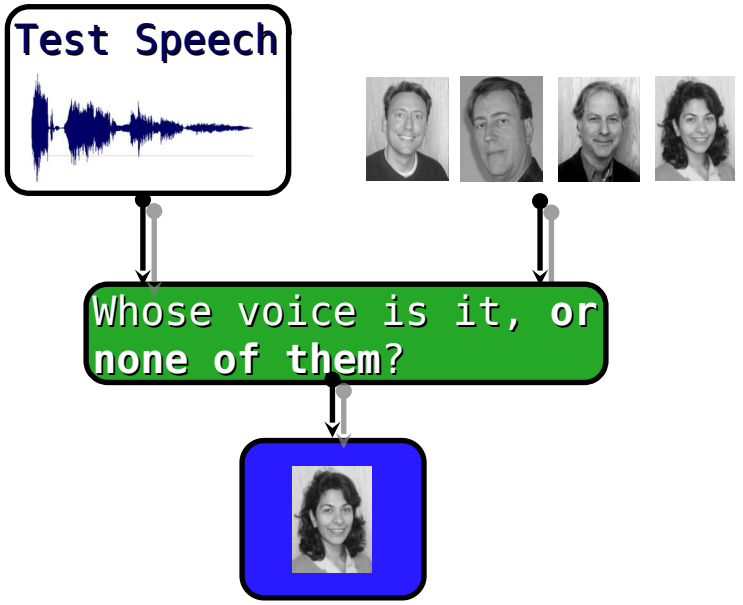
# Speaker identification

- Closed set speaker identification
  - We have training data for all speakers we are interested in
  - During test time, the speaker is guaranteed to be one of those speakers



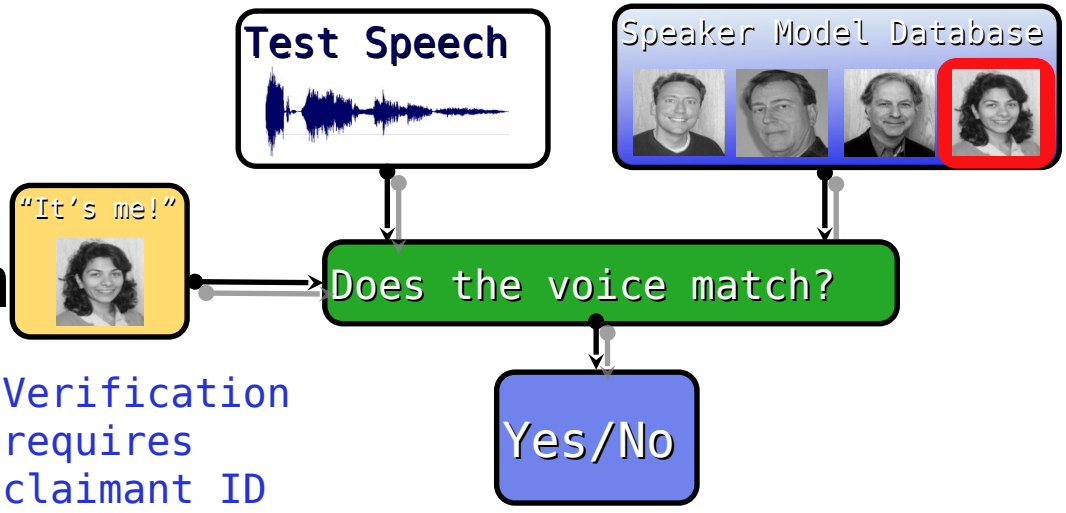
# Speaker identification

- Open set speaker identification
  - We have training data for all speakers we are interested in
  - During test time, the speaker is **not** guaranteed to be one of those speakers



# Speaker verification

- User claims an identity
- System task: Accept or reject identity claim
- The voice can come from outside the set of known speakers

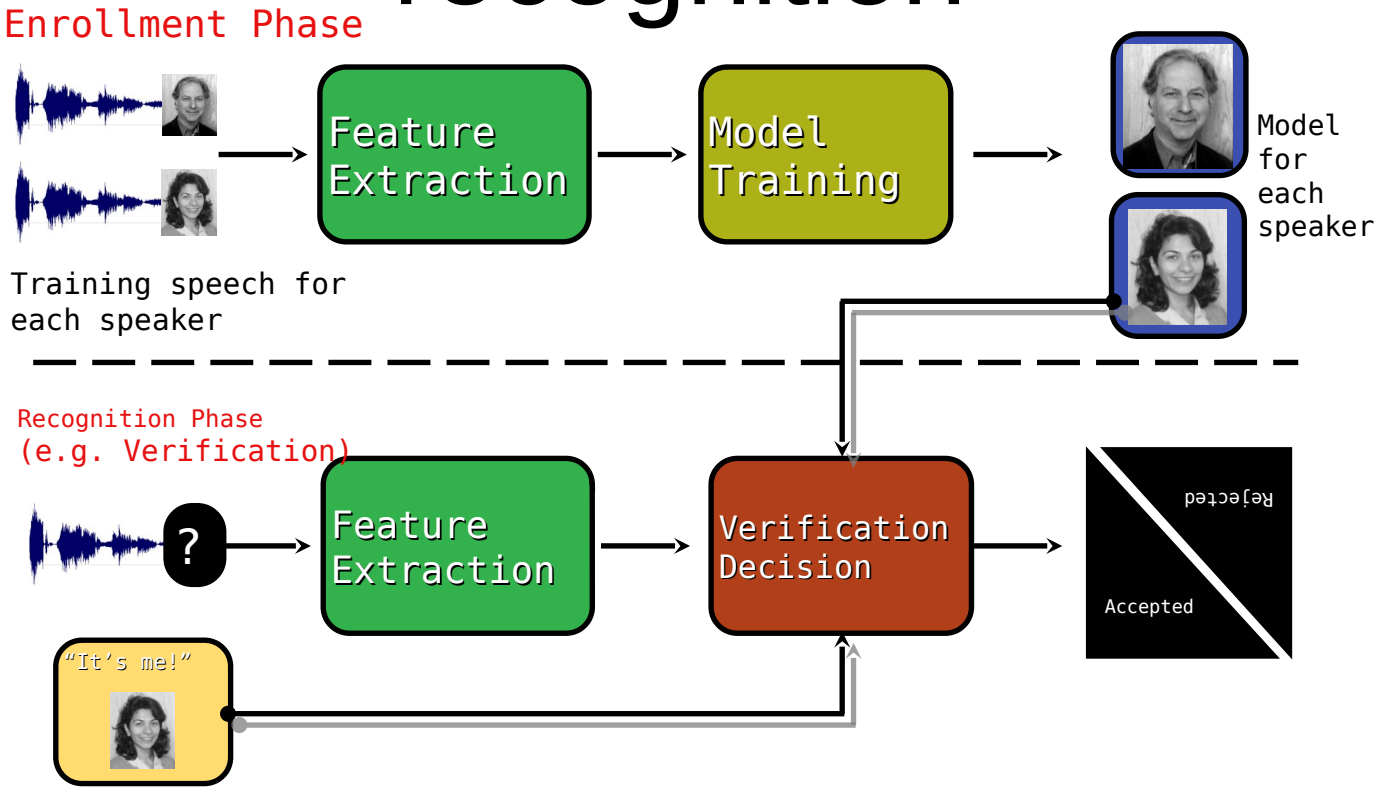


# Speaker verification types

- Text-independent recognition
  - Recognition system does not know text spoken by person
  - Examples: User selected phrase, conversational speech
  - Used for applications with less control over user input
  - More flexible system but also more difficult problem
  - Speech recognition can provide knowledge of spoken text
  - For example: telephone banking – use as an additional verification measure and apply during the conversation

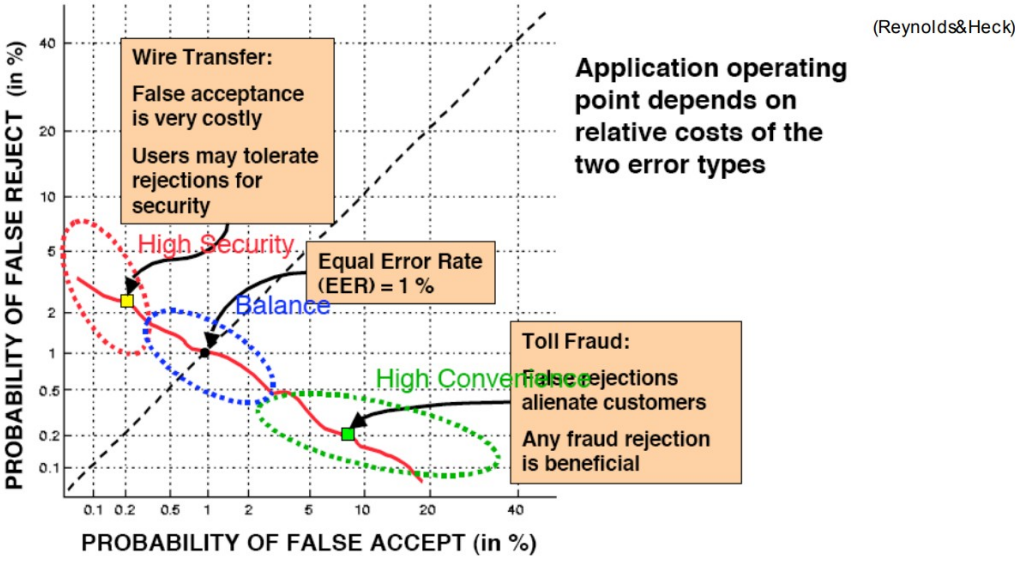
- Text-dependent recognition
  - Recognition system knows text spoken by person
  - Examples: password phrase, prompted phrase
  - Used for applications with strong control over user input
  - Knowledge of spoken text can improve system performance
  - Prompting may reduce risk of imposters using voice recordings (spoofing)

# Verification: enrollment and recognition



# Speaker verification operation point

- Speaker verification performance is often measured in terms of equal error rate (EER)
  - a decision threshold that produces equal number of false rejects and false accepts
- The actual decision threshold (operation point) is highly dependent on the application
  - Are false rejects or false accepts more costly?



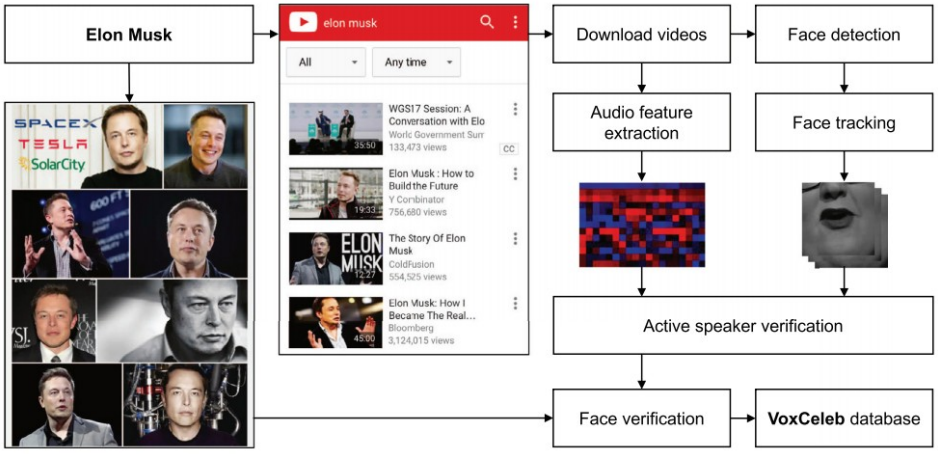
# Speaker verification: modern approach

- Modern speaker recognition is purely based on pretrained models
  - Large (possibly out-of-domain) speaker-labeled speech dataset is used to train an utterance-to-speaker classifier
  - The final classifier layer is then thrown away, and the second-to-last layer output is used as an utterance embedding extractor
  - Utterance embeddings of enrollement and test utterances can now be compared
    - If they are similar (above some tuned threshold), the speaker is verified

- Research questions:
  - Where to get this large speech dataset?
  - How to reduce the effect of domain mismatch (e.g,: the embeddings are trained on English, but we want to apply it for Estonian: will it work?)
  - What is the optimal architecture of the speaker classification/embedding model and how to train it so that it will be most useful as an embedding extractor?
  - How to compute similarity between embeddings, possibly in mismatched conditions (e.g.: enrollment is silent environment, test utterance in a car)

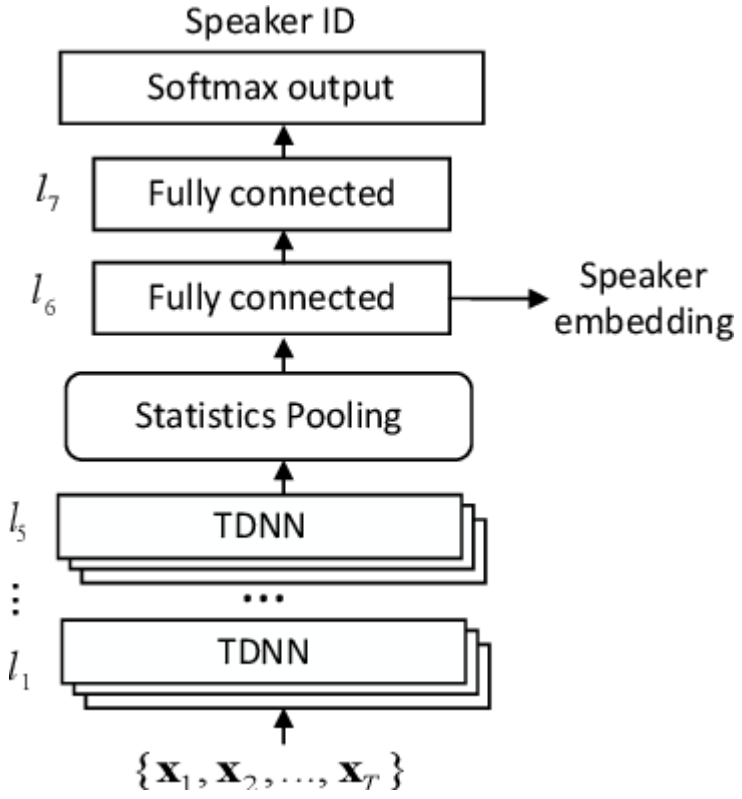
# VoxCeleb dataset

- How to get a free, diverse, and very large dataset for pretraining?
- VoxCeleb (1, 2): automatically collected dataset of 7000+ speakers, 2500+ hours
- Collection process:
  - Compile a list of celebrities with known faces (based on VGGFace dataset): from actors and sportspeople to politicians
  - Search for „<name> interview” on YouTube
  - Download videos
  - Find segments in the videos where the face of <name> appears
  - Active speaker verification: determine the audio-video synchronisation between mouth motion and speech in a video
  - Extract all such segments and label them with <name>



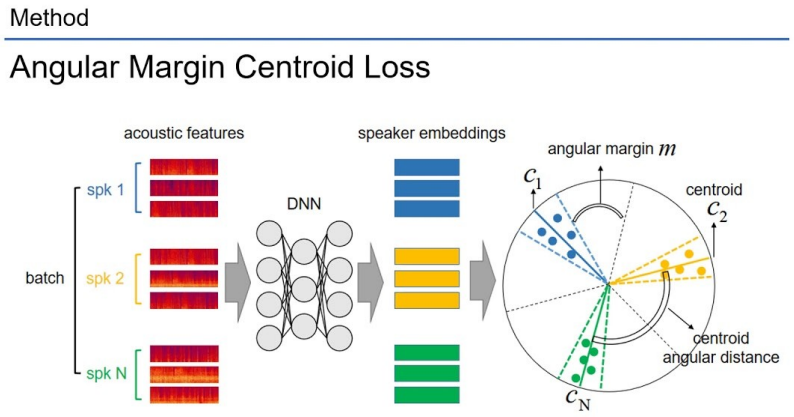
# X-vector model

- A breakthough in speaker recognition (2018)
- Architecture:
  - Input: filterbank features (same as in speech recognition)
  - Several layers of frame level 1D convolutional layers (called TDNNs in the paper)
  - Statistics pooling layer: computes mean and stddev over the utterance of each feature extracted by the last convolutional layer (i.e., like conventional average pooling, but also adds stddev for each feature)
  - Two utterance level fully connected layers
  - Softmax
- Speaker embeddings are extracted the from penultimate fully connected layer
- Must be trained with heavy data augmentation:
  - Take training data, and make several copes of it, with:
    - Take a random 3-second cut from the training utterances (makes the training more challenging for the model)
    - Random room reverberation
    - Added background noise
    - Added background music
    - Added „babble” noise
- Only works when training dataset is large enough (e.g., VoxCeleb)



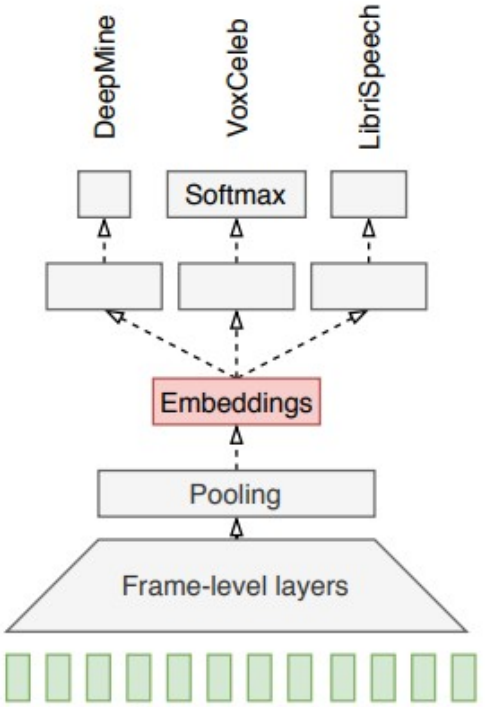
# Improvements to x-vector model

- Statistics pooling can be replaced with attention
  - This way, pooling is done only using the most relevant parts of the utterance
- 1D CNNs can be replaced with 2D CNNs (essentially the same as work well in image recognition)
- Don’t optimise cross-entropy loss, but the angular margin loss
  - I.e., the angle between the centroid of the speakers’ utterances in the embedding space
  - Benefit: speaker verification can be done by just comparing the angles between the enrollment centroid, and the test utterance



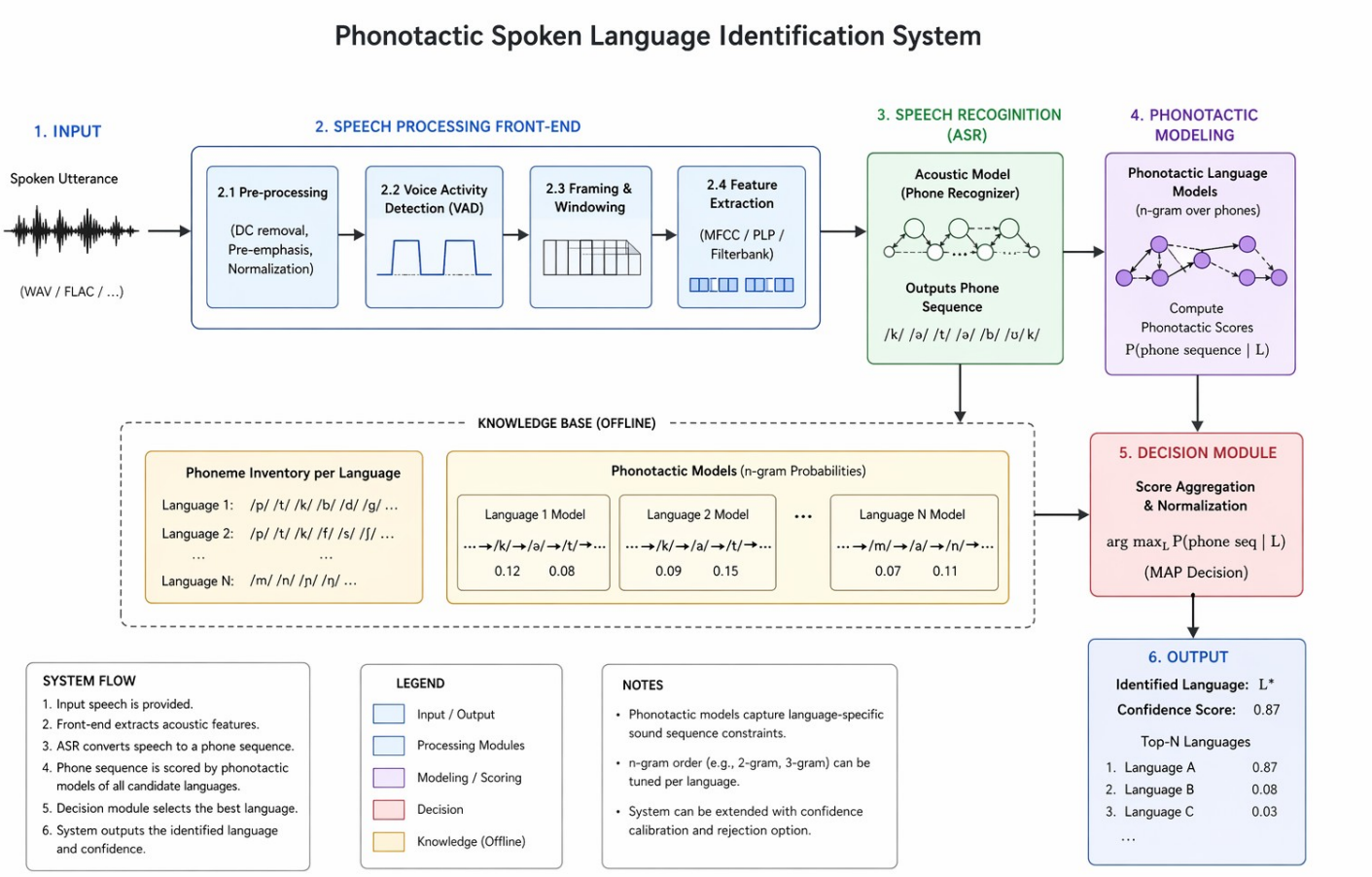
# Language portability of X-vectors

- Turns out that embeddings trained on VoxCeleb work pretty good for other languages as well
- But it’s better if you add some language-specific data
- However, it’s better to seperate the language-specific speakers (actually, all datasets with different characteristics) during training
  - I.e., each training dataset has it’s own output layer, and the speakers in the training data „compete” only with other speakers of the same dataset (Alumäe & Valk, 2020)
  - This way, language/dataset specific knowledge is pushed to the dataset-specific output layers and the embeddings are „encouraged” to be universal



# Spoken language recognition

Phonotactic language identification relies on the fact that different languages use different phonemes and combine them differently

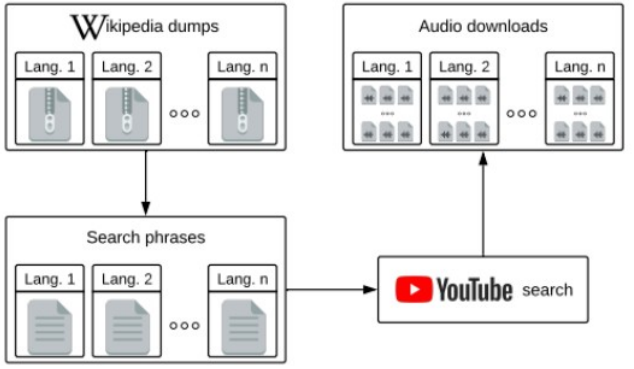


# Spoken language identification

- Modern spoken language identification is very similar to speaker recognition
  - X-vectors with modifications
  - Data augmentation during training
- Pretraining still helps:
  - E.g., use a very large language-labelled speech corpus to train a model for extracting embeddings
  - Only ~200 utterances per language are needed now to train a a new model for a new set of languages
  - But how/where to get this large language-labelled speech dataset?

# VoxLingua107

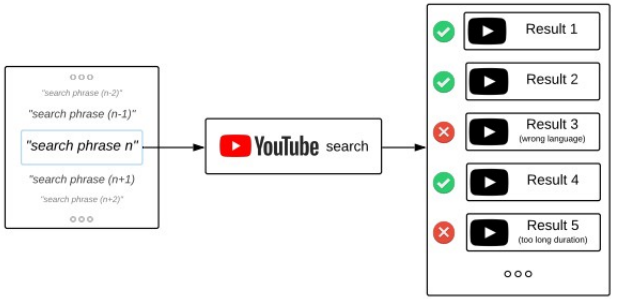
- Research done in our lab (Valk & Alumäe, 2020)
- Like VoxCeleb, but for language recognition
- A dataset of speech „from the wild” (YouTube) for 107 languages
- Collected automatically: random trigram search queries, based on Wikipedia of the particular language
- Idea: if the title and description of the video is in a particular language, then it likely contains speech from this language
- Text-based language identification model was used to filter out phrases that were not (confidently) in the expected language




| Language | Random search phrase |
|---|---|
| English | *the northern territory* |
| Estonian | *ameerika ühendriikide relvajõud* |
| Finnish | *hiileen liittynyt hydroksyyliryhmä* |
| German | *abgesetzten enameloliden zahnkappen* |
| Latvian | *starptautiskajā šaha turnīrā* |
| Russian | *совета рабочих депутатов* |
| Spanish | *administración del estado* |
| Urdu | انہ اور فرانس |

# VoxLingua107: post-processing

- Many steps to filter out noise (i.e., data not in the expected language):
  - Language identification applied to retrieved video title and description
  - Speech/non-speech detection to filter out music
  - Speech segments were split into utterances of max 20 second duration
- A random subset of the data was manually verified by volunteers
  - 85% of utterances in the expected language
- Data-driven classifier was used to remove outliers
  - Result: 98% of utterances in the expected language



# VoxLingua107: facts

| Language | h | Language | h | Language | h | Language | h | Language | h | Language | h | Language | h |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Abkhazian | 10 | Catalan | 88 | German | 39 | Kannada | 46 | Marathi | 85 | Shona | 30 | Tibetan | 101 |
| Afrikaans | 108 | Cebuano | 6 | Greek | 66 | Kazakh | 78 | Mongolian | 71 | Sindhi | 84 | Turkish | 59 |
| Albanian | 71 | C. Khmer | 41 | Guarani | 2 | Korean | 77 | Nepali | 72 | Sinhala | 67 | Turkmen | 85 |
| Amharic | 81 | Chinese | 44 | Gujarati | 46 | Lao | 42 | Norwegian | 107 | Slovak | 40 | Ukrainian | 52 |
| Arabic | 59 | Croatian | 118 | Haitian | 96 | Latin | 67 | Nynorsk | 57 | Slovenian | 121 | Urdu | 42 |
| Armenian | 69 | Czech | 67 | Hausa | 93 | Latvian | 42 | Occitan | 15 | Somali | 103 | Uzbek | 45 |
| Assamese | 155 | Danish | 28 | Hawaiian | 12 | Lingala | 90 | Panjabi | 54 | Spanish | 39 | Vietnamese | 64 |
| Azerbaijani | 58 | Dutch | 40 | Hebrew | 96 | Lithuanian | 82 | Persian | 56 | Sundanese | 64 | Waray | 11 |
| Bashkir | 58 | English | 49 | Hindi | 81 | Luxembourg. | 75 | Polish | 80 | Swahili | 64 | Welsh | 76 |
| Basque | 29 | Esperanto | 10 | Hungarian | 73 | Macedonian | 112 | Portuguese | 64 | Swedish | 34 | Yiddish | 46 |
| Belarusian | 133 | Estonian | 38 | Icelandic | 92 | Malagasy | 109 | Pushto | 47 | Tagalog | 93 | Yoruba | 94 |
| Bengali | 55 | Faroese | 67 | Indonesian | 40 | Malay | 83 | Romanian | 65 | Tajik | 64 | **Total** | **6628** |
| Bosnian | 105 | Finnish | 33 | Interlingua | 3 | Malayalam | 47 | Russian | 73 | Tamil | 51 | **Average** | **62** |
| Breton | 44 | French | 67 | Italian | 51 | Maltese | 66 | Sanskrit | 15 | Tatar | 103 | | |
| Bulgarian | 50 | Galician | 72 | Japanese | 56 | Manx | 4 | Scots | 3 | Telugu | 77 | | |
| Burmese | 41 | Georgian | 98 | Javanese | 53 | Maori | 34 | Serbian | 50 | Thai | 61 | | |

# VoxLingua107: results

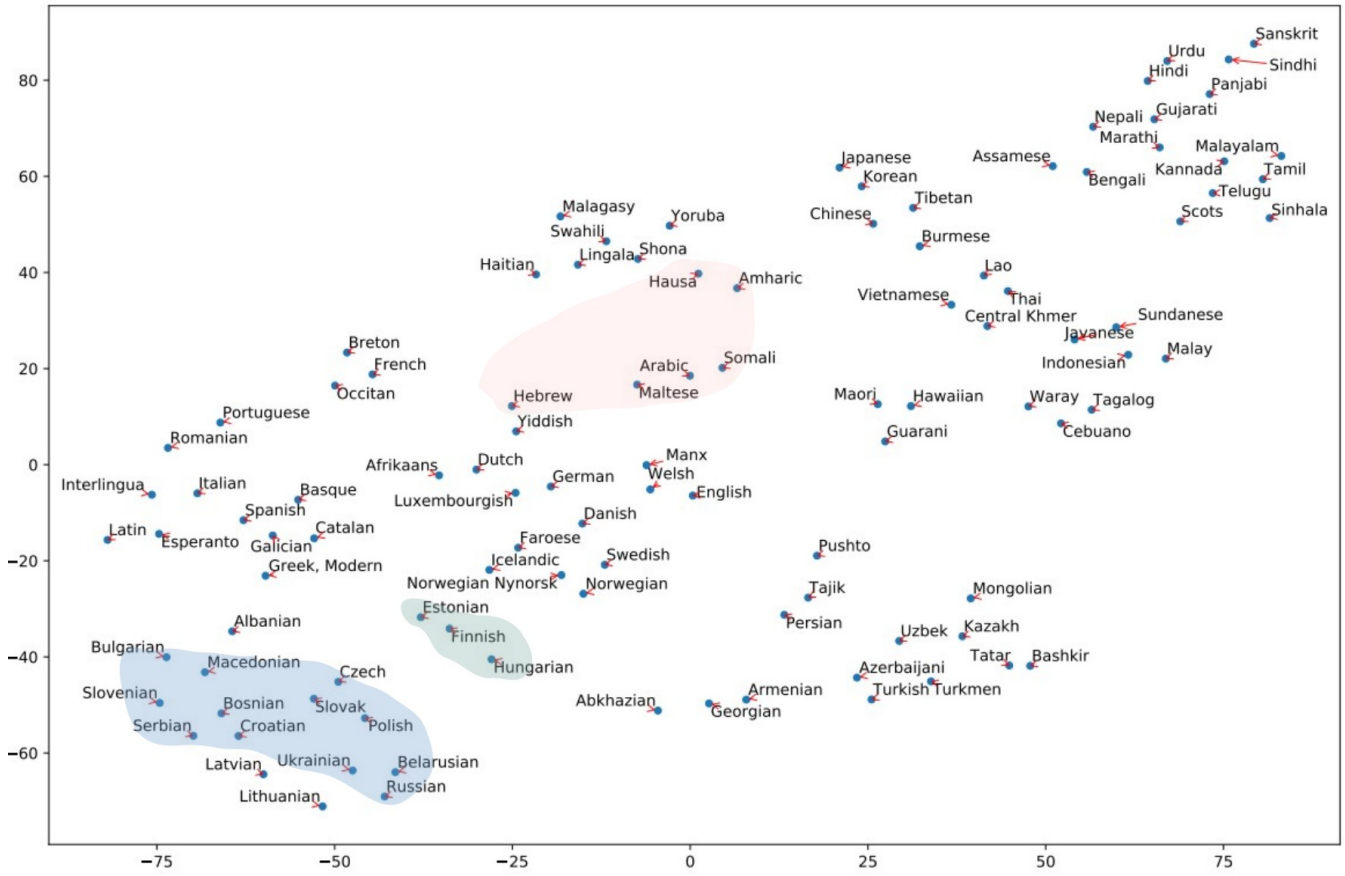
- Result: 7.6% error rate
- Try it yourself: https://huggingface.co/speechbrain/lang-id-voxlingua107-ecapa
- Data available here: http://bark.phon.ioc.ee/voxlingua107/
- Pretrained model available here: https://huggingface.co/speechbrain/lang-id-voxlingua107-ecapa

| |
|---|
| Urdu → Hindi |
| Spanish → Galician |
| Norwegian → Nynorsk |
| Dutch → Afrikaans |
| English → Welsh |
| Estonian → Finnish |

**Most common errors**

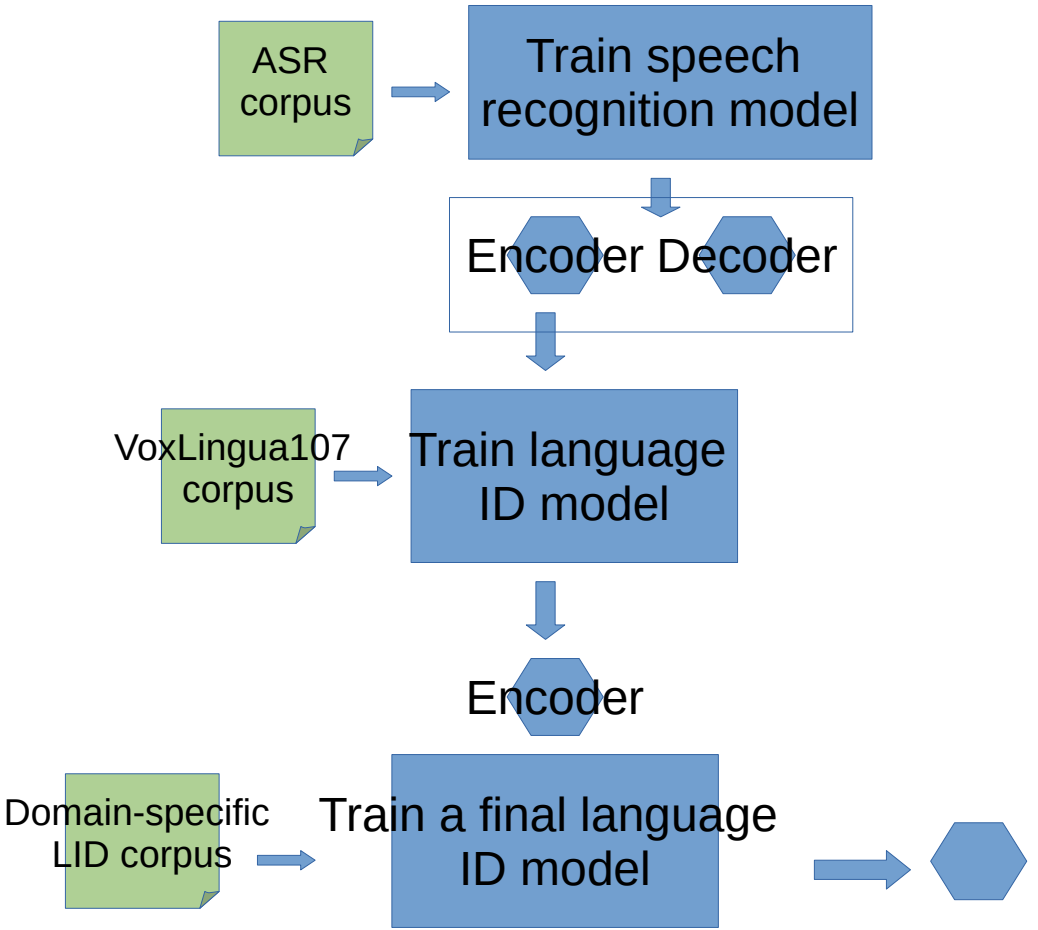
# VoxLingua107: side effect

- t-SNE projection of language embeddings, avaraged over language training data
- Reflects the true hierarchy of language families
- Some obvious deviations, likely due to geographical and cultural influences
- E.g., Slavic, Finno-Ugric and Afroasiatic groups



# Language ID benefits from ASR

- Language identification system can be pretrained on a speech recognition task
- Pipeline:
  - Train an encode-decoder ASR model on some data (multilingual, or just a very large and diverse monolingual corpus)
  - Throw away decoder, use encoder as a finetunable feature extractor
  - Add attention-based pooling mechanism, train a language ID system on VoxLingua107
  - Result: very good feature extractor for (almost) any language ID task



# Language ID benefits from ASR, II

- Task 1: closed-set language ID task with 6 languages (Cantonese, Korean, Indonesian, Vietnamese, Russian), training data 10h per language
- Task 2: noisy language ID task with 5 Asian languages (10h per language)
- Task 3: 11 South-African languages (Afrikaans, English, isiNdebele, isiXhosa, ..), 2 hours training data per language
- Table shows error rates

| | Task 1 | Task 2 | Task 3 |
|---|---|---|---|
| Trained only on task training data | 11.9 | 6.8 | 26.4 |
| Pretrained on VoxLingua107 | 2.8 | 1.3 | 12.4 |
| + First pretrained on Mozilla CommonVoice (multilingual ASR) | 0.6 | 0.8 | 10.1 |
| + First pretrained on WeNetSpeech (10K hour Mandarin ASR corpus | 0.8 | 0.4 | 9.7 |

# Some general Tips & Tricks about Training neural Networks

Partly based on Andrej Karpathy's (Head of AI at Tesla at that time) blog post http://karpathy.github.io/2019/04/25/recipe/ (must read)

# Data

- Become one with data
  - Inspect your data carefully (spend many hours)
  - Understand the distribution and look at the patterns
    - Your brain is very good at it
    - Are there duplicates?
    - Are there corrupt examples?
    - Are the labels inbalanced?
  - Think how your brain solves this task
    - Can you solve this task on local context only?
    - Or do you need larger (global) context?

# How much data?

- Very general rule: you can start thinking about training a DNN if you have at least 1000 training samples
- There is no data like more data
- Common situation:
  - Baseline accuracy with a simple model: accuracy 60%
  - Super-well tuned “transformer with multi-head attention”: accuracy: 70%
    - Spend 1 week
  - Simple model with more data: 80%
    - Spend 2 days on data collection
- Spending time on data collection is a time well spent
  - Can always apply new models / training tricks when they are invented
  - Time spent on fine-tuning a fancy model might be wasted when suddenly a new model architecture is invented

# Data augmentation

- *“The next best thing to real data is half-fake data”*
- Data augmentation: train artificial additional training data by corrupting the real data by some domain-specific way
- Often applied so that the amount of training data is increased 10 (or more) times
- Data augmentation can make a huge difference, especially if domain adaptation can be performed using augmentation

# Data augmentation, continued

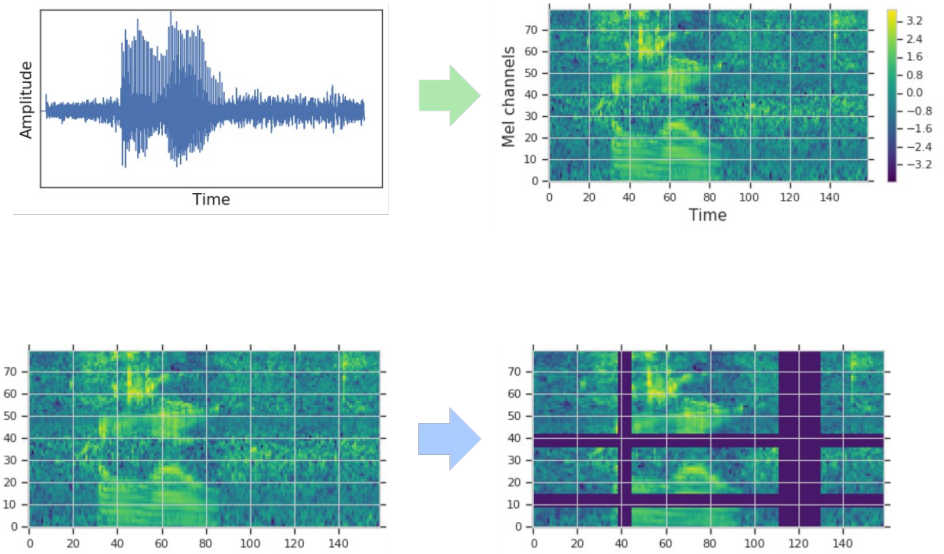
- For example:
  - Speech recognition model trained on clean data: accuracy on reverberant/noisy data **50%**
  - Add noise and reverberate clean training data: accuracy **85%**
- Data augmentation is more useful in domains where input data is “continuous”
  - Image processing
  - Speech processing
- Usually works better than trying to “fix” the test data (e.g., denoise)
- Almost never hurts accuracy

# Data augmentation is speech recognition

- Speed perturbation
  - Add copies of training sentences, sped up or slown down by 10%
  - Simulates faster/slower speaking, but also different vocal tract characteristics
- Reverberation
  - Add room effects (using real or artificial **impulse responses**)
- Noise augmentation
  - Add background noise to (clean training data), e.g. street noise, engine, car, wind
  - Add “foreground noises” (e.g., door slams, claps, clicks)
  - Add music
  - Add “babble noise” (many persons speaking in the background)
  - All this with random signal-to-noise ratio, and many times

# Spectral augmentation

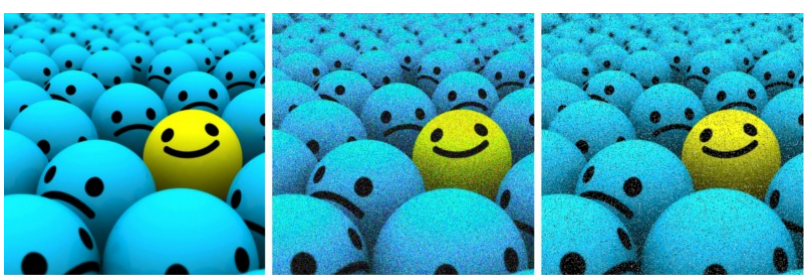
- Proposed by Google researchers https://ai.googleblog.com/2019/04/specaugment-new-data-augmentation.html
- Three types of modifications of the raw filterbank spectrogram, randomly chosen
  - Time warping
  - Masking blocks of consecutive filterbank features (horizontal)
  - Masking whole filterbank blocks in time (vertical)

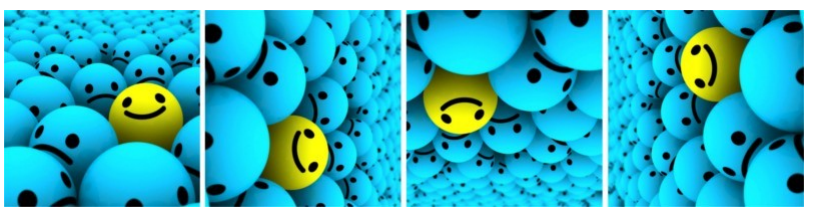



| | LibriSpeech 960h | | Switchboard 300h | |
|---|---|---|---|---|
| | test-clean | test-other | Switchboard | CallHome |
| Previous SOTA | 2.95 | 7.50 | 8.3 | 17.3 |
| Our Results | **2.5** | **5.8** | **6.8** | **14.1** |

# Data augmentation with images

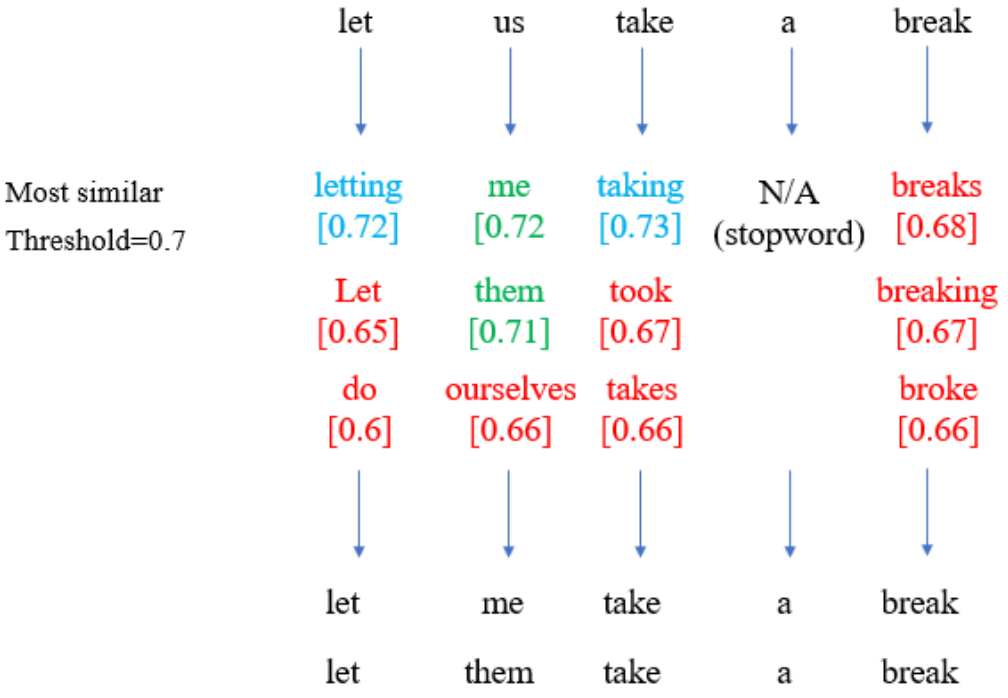
- Flipping
- Rotation
- Translation
- Scaling
- Adding noise
- ...





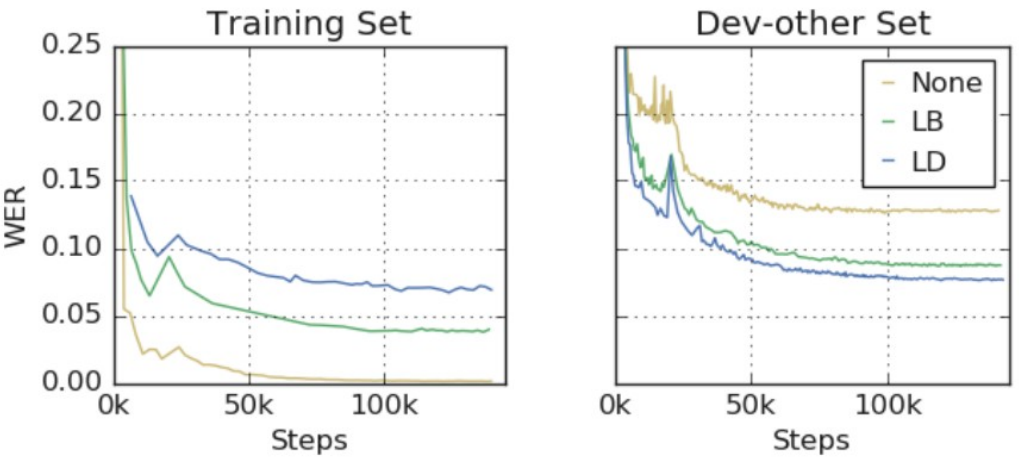
# Data augmentation for NLP

- For text data, data augmentation is less useful
- One idea: replace words in training data with words that have similar embeddings
  - But usually better to just use pretrained word embeddings (or pretrained contextualized representations, like BERT)
- Alternative: use domain knowledge
  - E.g., replace company names in text with other company names from the business registry (if having a good coverage of company names is relevant to your task)
- Or: use machine translation and backtranslation:
  - Original:
    *The restaurant serves huge breakfast for a very cheap price.*
  - Translated to German and back:
    *The restaurant serves a huge breakfast at a very reasonable price.*
  - Translated to Japanese and back:
    *A rich breakfast is served at the restaurant at an affordable price.*



# Data augmentation under-fits training data

- Data augmentation turns over-fitting problem into under-fitting problem
  - Loss when training augmented data is worse than when training on clean data
  - But loss (and error rate) on test data is better
- Thus, common methods that work against under-fitting help:
  - Using larger (wider and deeper) models
  - Training for more epochs

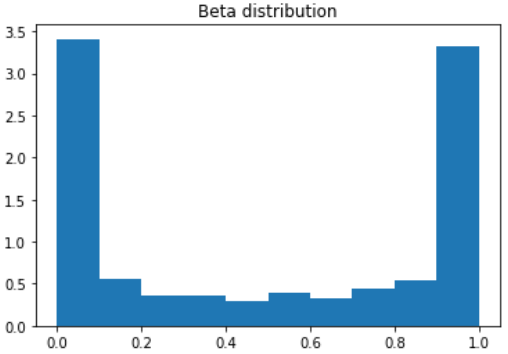


# Mixup

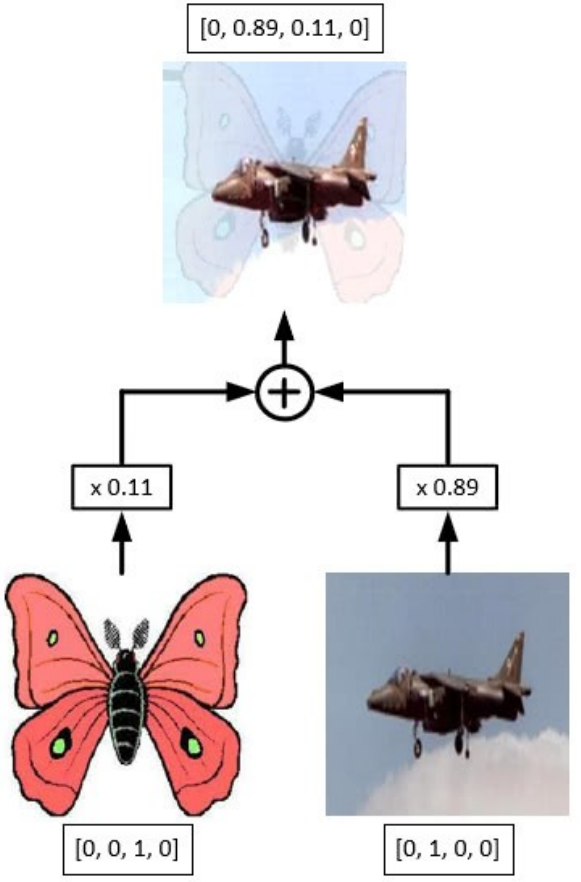
- During training, mix two training samples and the corresponding labels

$$\tilde{x} = \lambda x_i + (1 - \lambda) x_j, \quad \text{where } x_i, x_j \text{ are raw input vectors}$$
$$\tilde{y} = \lambda y_i + (1 - \lambda) y_j, \quad \text{where } y_i, y_j \text{ are one-hot label encodings}$$

- The mixup factor is drawn randomly from a beta distribution




- Kind of surprising that it helps
- Not really applicable to text data

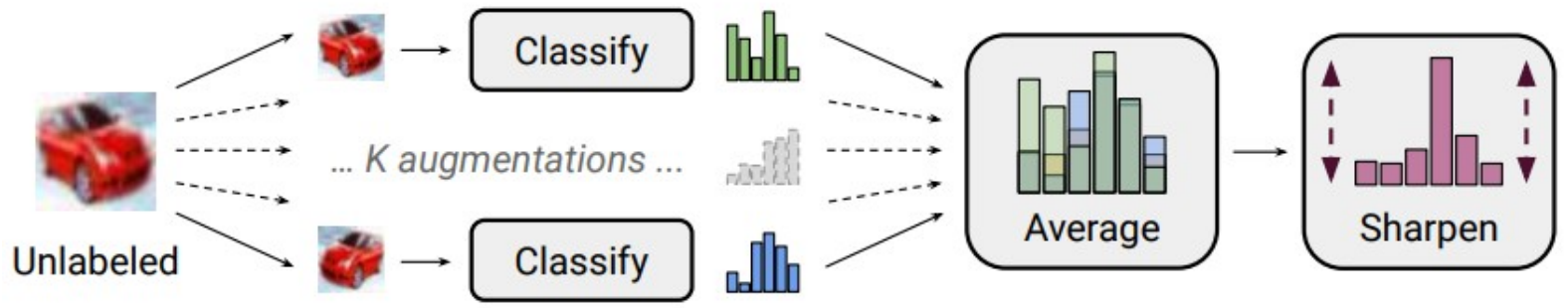


# MixMatch: semi-supervised training

Given: some **labeled data** and a lot of **unlabeled data**

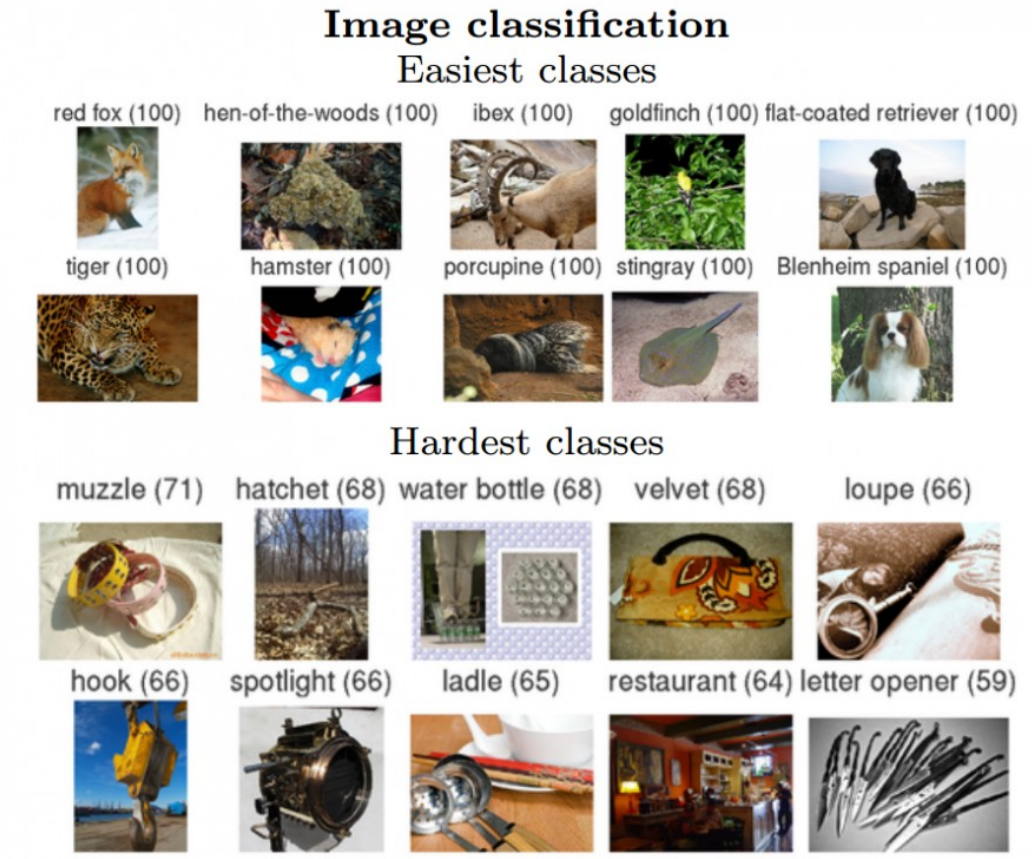
Procedure:

- Train a first model on labeled data (with data augmentation)
- Generate pseudo-labels for unlabeled data
  - This is done by classifying different augmentations of the unlabeled sample, averaging the predictions and sharpening the resulting probability distribution (to make it less smooth and more one-hot-like), see below
- Train a new model, using mixup between labeled and pseudo-labeled samples



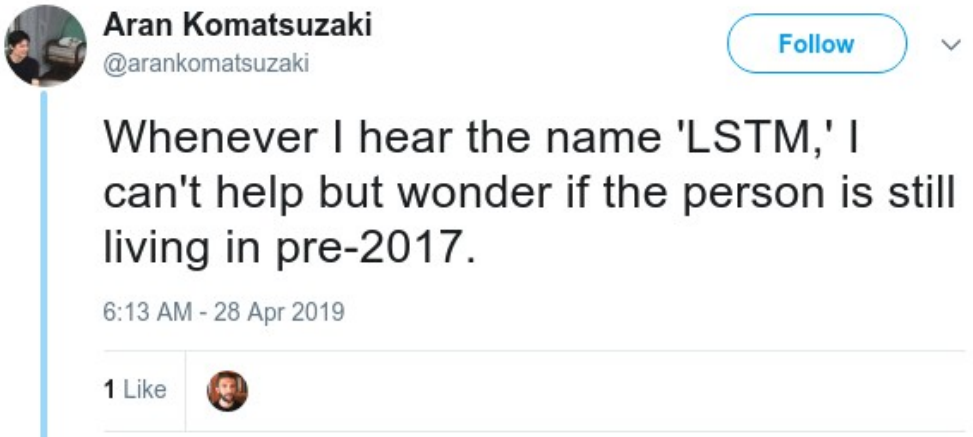
# Pretraining

- *It rarely ever hurts to use a pretrained network if you can, even if you have enough data*
- Pretraining was first popularized by the image recognition community
  - Pretrain a ConvNet on ImageNet
  - ImageNet: dataset of 1.2M images, 1000 categories
  - Models trained on ImageNet can be used to initialize models **for completely other datasets** and improve performance significantly
  - Works even if you have only a few examples per object



# What model to use in NLP?

- What model to use for NLP task (e.g. text classification, information extraction), given that you have reasonable amount of training data?
- For most NLP tasks, **Transformer** (multi-layer multi-head attention with position encodings) is currently the best choice
- For English, use BERT (or some of its descendants, like XLM-Roberta) for getting contextualized word embeddings
- For Estonian, try XML-Roberta and EstBERT
- Consider machine translation, if you can afford
  - Many hard tasks work much better in English, due to abundance of training data
  - For example, abstractive summarization: translate Estonian test data to English, apply an English summarization model, and translate results back to Estonian
  - Works better than an Estonian model trained on little data, despite MT errors



# Debugging neural networks

- *Neural net training fails silently*
- Tricky to unit test
- Your net can still (shockingly) work pretty well even if your training data is corrupted somehow
  - E.g., maybe you feed it columns instead of rows of data
  - It’s because neural nets can memorize the data to some extent
- Most of the time when you screw something up, it will train but silently work a bit worse

# Recipe for training neural nets

- Verify your data
- Start with simple models
  - No data augmentation, fancy learning rate schedules, etc
- Train an input-independent baseline, (e.g. easiest is to just set all your inputs to zero)
  - This should perform worse than when you actually plug in your data without zeroing it out. Does it?
- Overfit a single batch of only a few examples (e.g. as little as two).
  - Verify that we can reach the lowest achievable loss (e.g. zero)

# Recipe, continued

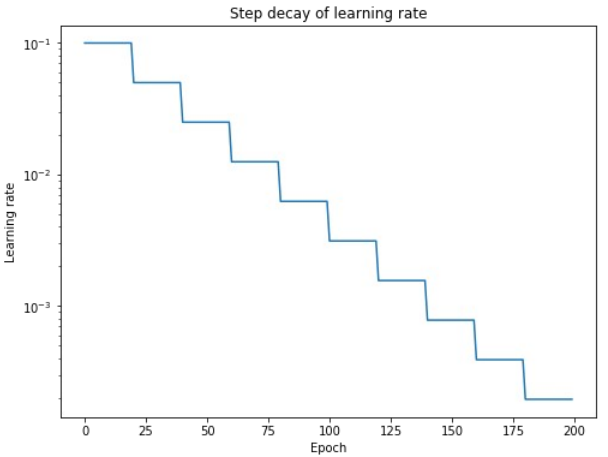
- Don’t be a hero
  - Start with a model that is known to give good results on similar tasks
  - You’re allowed to do something more custom later and beat this
- One complexity at a time
  - At fanciness to your model one by one and make sure it improves the model
- Leave learning rate tuning to the end

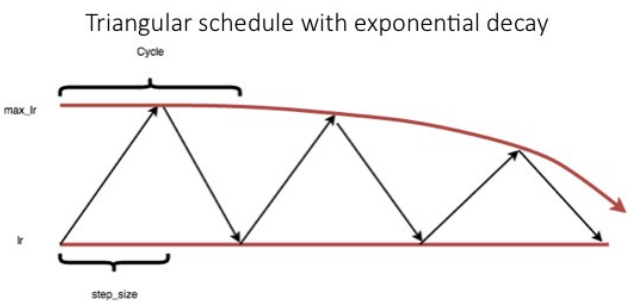
# Recipe, continued

- Regularize (avoid overfitting)
  - Try to get more data
  - Data augmentation, try to be creative
  - Pretraining rarely hurts
  - Semisupervised learning usually gives very little improvement, and is very complicated
    - But recently big progress
  - Try with less features
  - Try smaller model size
  - Add dropout
  - Add L2 regularization (weight decay)
  - Early stopping
  - Try larger model, but stop early

# Some tricks: learning rate schedule

- Learning rate schedule
  - E.g., step decay  (0.1 at the beginning, 0.0001 at the end)
  - Or: constant learning rate, but decrease it when the loss on dev data doesn't decrease any more (`ReduceLROnPlateau` in Pytorch)
  - More recent: triangular learning rates
    - Start at learning rate 0.001
    - Gradually increase it to 0.01 at epoch 25%
    - Then gradually decrease it until the end
  - Cyclic learning rates



# Some tricks: dropout, label smoothing

- Similarly to learning rate, dropout can be also scheduled
  - E.g.: 0 dropout at the beginning,
  - Increase dropout gradually to 0.3 at epoch 50%
  - Then gradually decrease it back to 0

- Label smoothing
  - Very simple idea: redistribute 0.1 of probability mass from the correct label to all other labels
  - Often used in Google's papers
  - Results in less loss fluctuations on dev data during epochs in my experience
  - Maybe disable label smoothing during the last training phase

# Ensembles

- *Model ensembles are a pretty much guaranteed way to gain 2% of accuracy on anything*
  - Ensembles of models of different architecture result in the best performance
  - Even if a particular model is relatively bad (compared to the best ones in the ensemble), combining its predictions with others can give surprising gains
- *If you can't afford the computation at test time, try distilling your ensemble into a network using knowledge distillation*
  - Compute posteriors (target probabilities) for your training data using the ensemble, and train a final model on the posteriors (instead of real targets)
  - This way, the final model learns to mimic the ensemble