

Test slide

- Is there a chat box?
- Can you see my pointer?
- Can you hear this: Play

Learning acoustic units and words from unlabelled speech (with a bit of vision)

CLSP Seminar, Johns Hopkins University, Oct. 2020

Herman Kamper

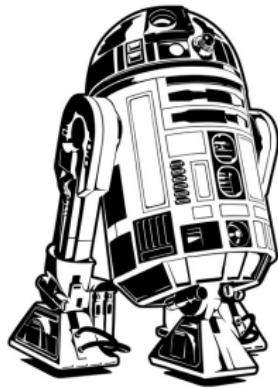
E&E Engineering, Stellenbosch University, South Africa

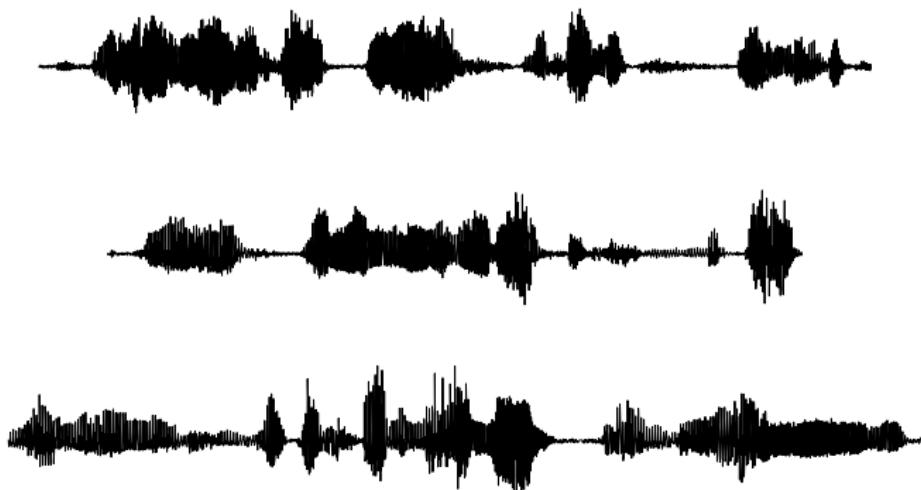
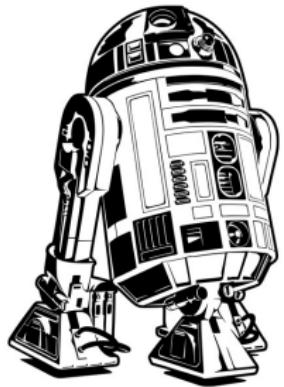
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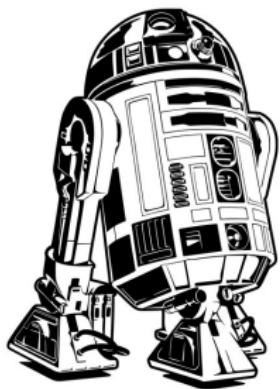


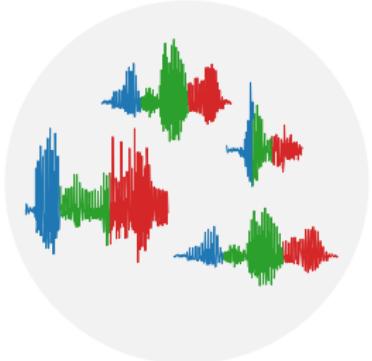
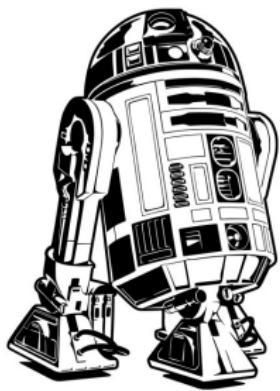


Photo: Leon Croukamp











Why unsupervised speech processing?

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Bootstrap low-resource speech technology

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Bootstrap low-resource speech technology



Applications such as non-parallel voice conversion

Why unsupervised speech processing?



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Applications such as non-parallel voice conversion



Cognitive models of language acquisition

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New insights and modelling approaches

Experience Grounds Language

Yonatan Bisk*

Ari Holtzman*

Jesse Thomason*

Jacob Andreas

Yoshua Bengio

Joyce Chai

Mirella Lapata

Angeliki Lazaridou Jonathan May Aleksandr Nisnevich Nicolas Pinto Joseph Turian

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You can't learn language ...

... from the radio (internet). $\text{WS2} \subset \text{WS3}$

*A learner cannot be said to be in WS3
if it can perform its task without sensory
perception such as visual, auditory, or
tactile information.*

... from a television. $\text{WS3} \subset \text{WS4}$

*A learner cannot be said to be in WS4
if the space of actions and consequences
of its environment can be enumerated.*

... by yourself. $\text{WS4} \subset \text{WS5}$

*A learner cannot be said to be in WS5 if
its cooperators can be replaced with clev-
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A learner cannot be said to be in WS3 if it can perform its task without sensory perception such as visual, auditory, or tactile information.

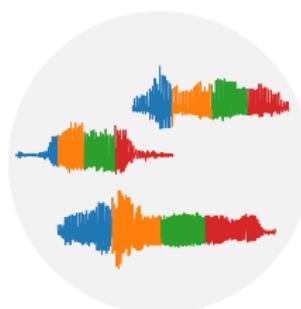
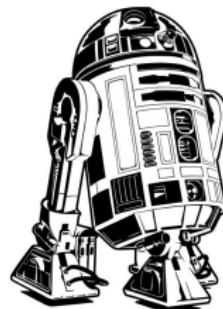
... from a television. $WS3 \subset WS4$

A learner cannot be said to be in WS4 if the space of actions and consequences of its environment can be enumerated.

... by yourself. $WS4 \subset WS5$

A learner cannot be said to be in WS5 if its cooperators can be replaced with cleverly pre-programmed agents to achieve the same goals.

But what can (and should) we learn at these different levels?



Levels of language learning (for word and phone acquisition)

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1. Vector-quantised neural networks for unsupervised acoustic unit discovery

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Benjamin
van Niekerk



Leanne
Nortje

1. Vector-quantised neural networks for unsupervised acoustic unit discovery



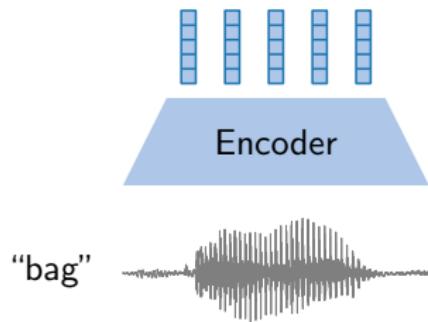
Benjamin
van Niekerk



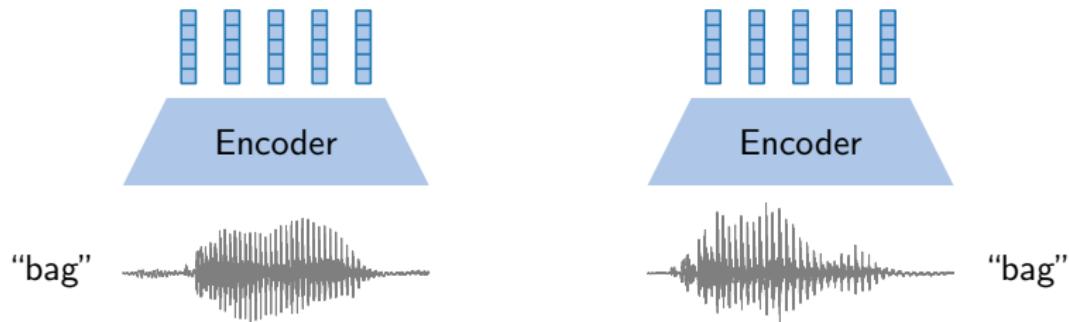
Leanne
Nortje

Phonetic representation learning

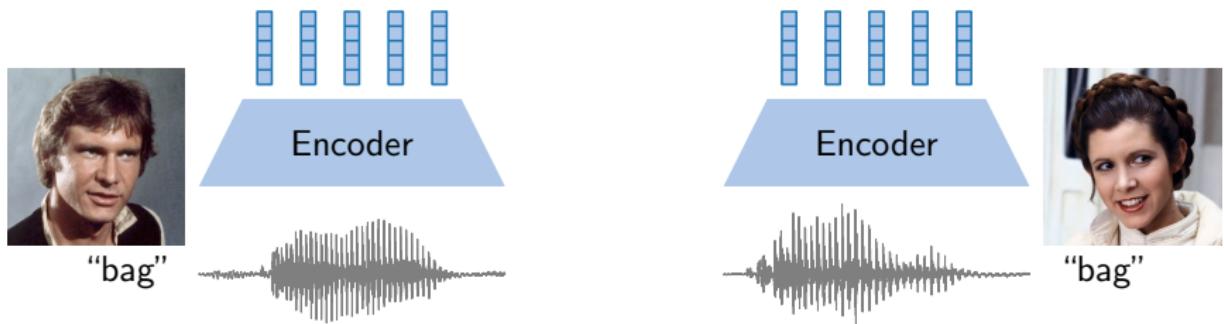
Phonetic representation learning



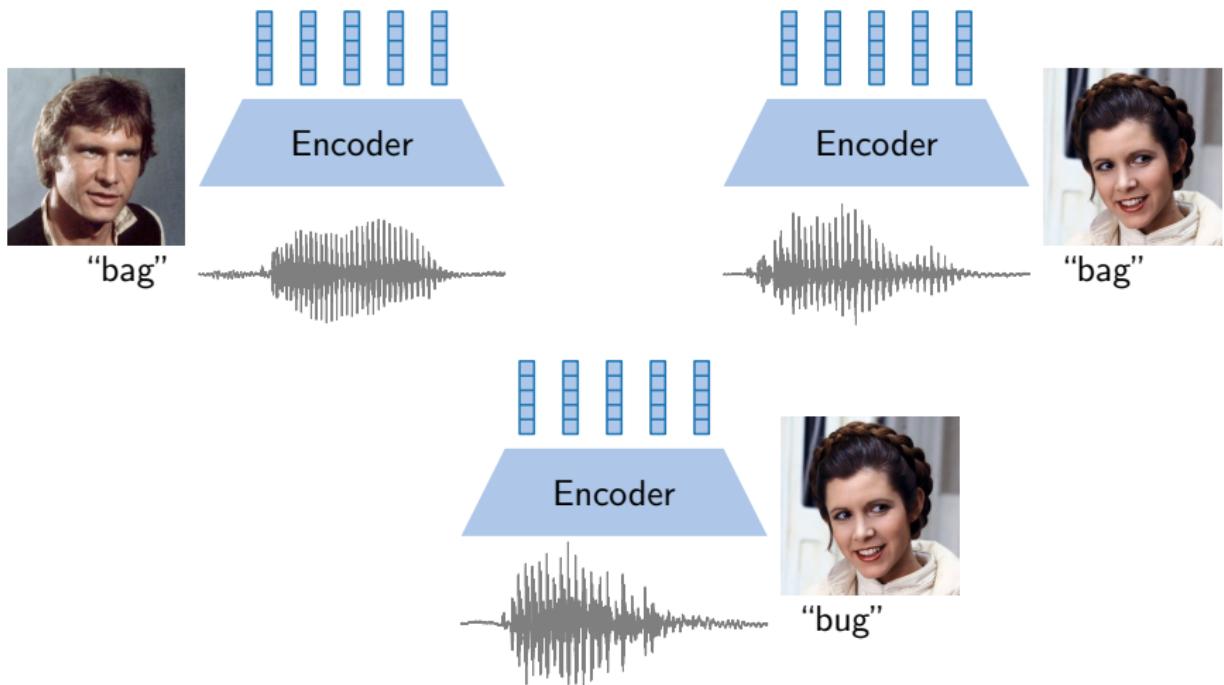
Phonetic representation learning



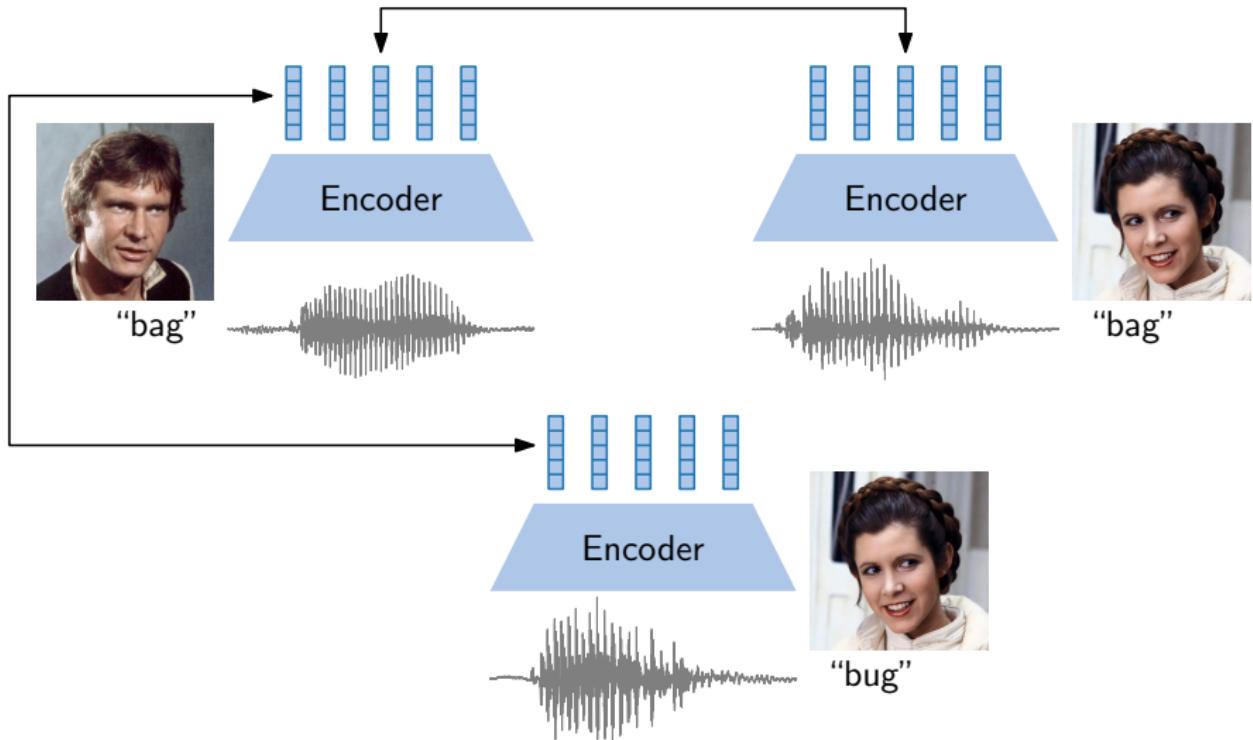
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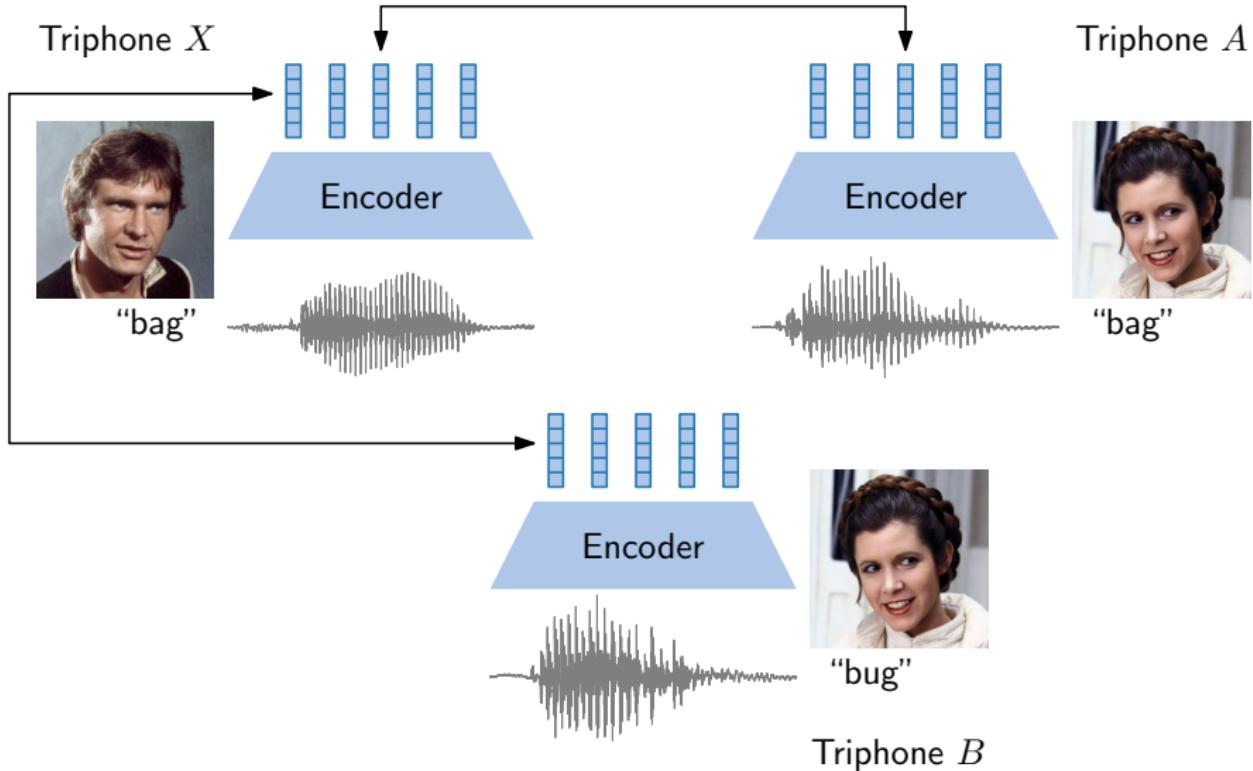
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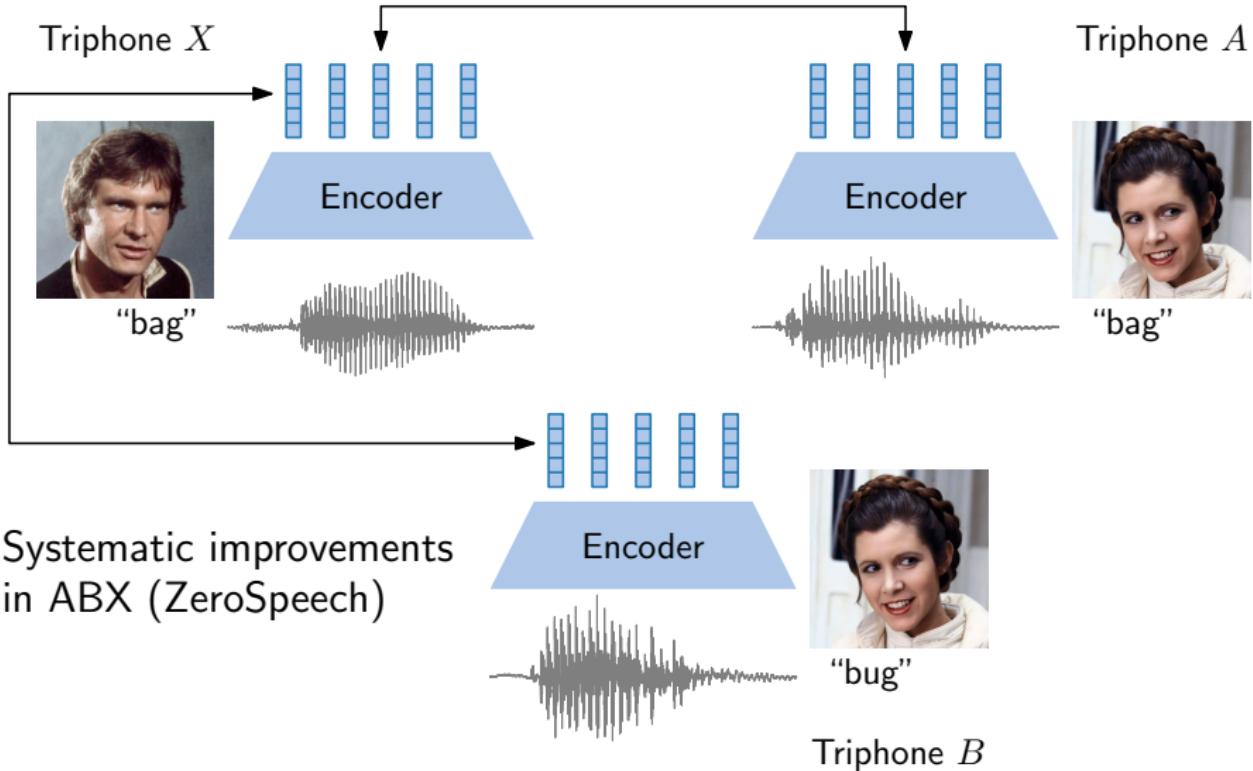
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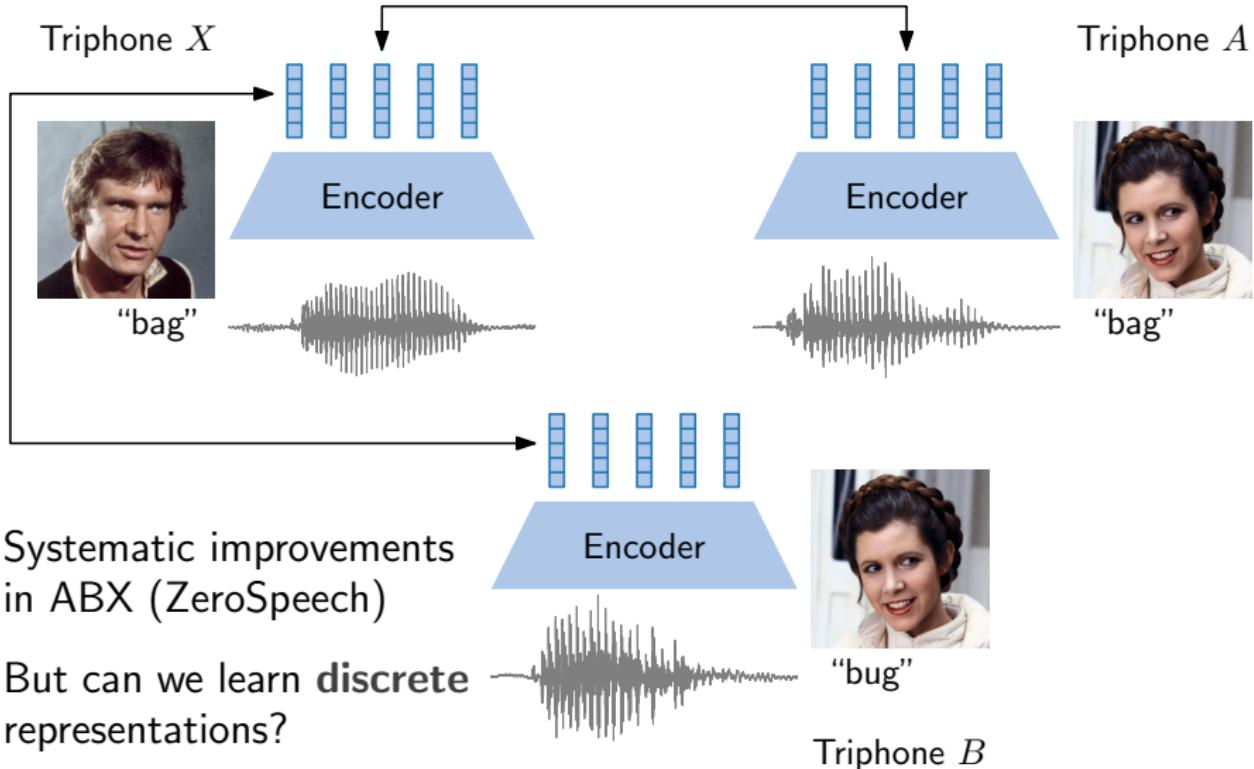
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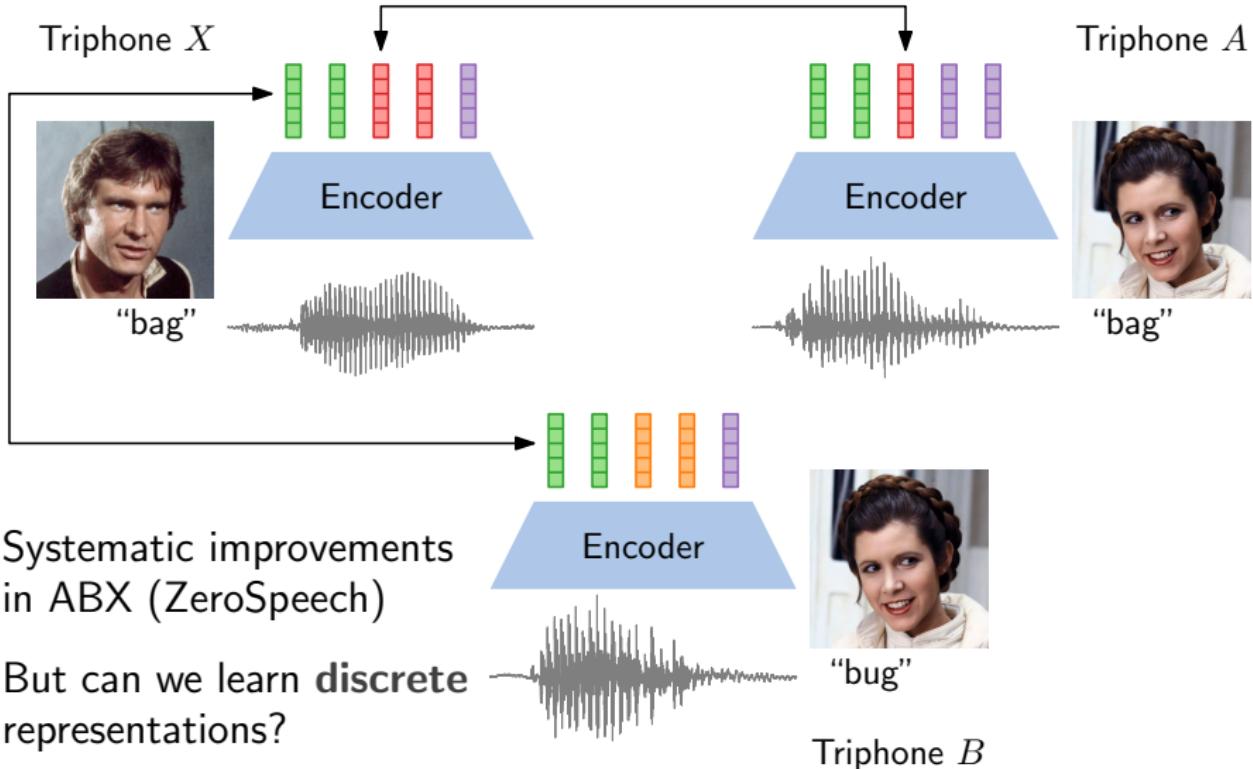
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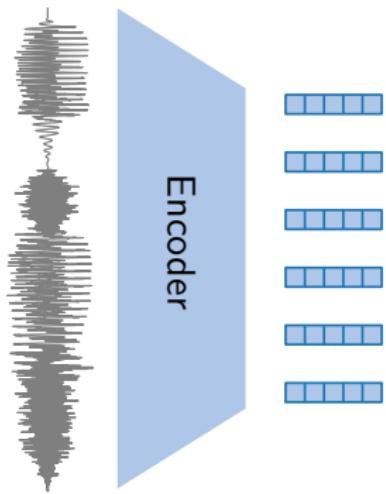


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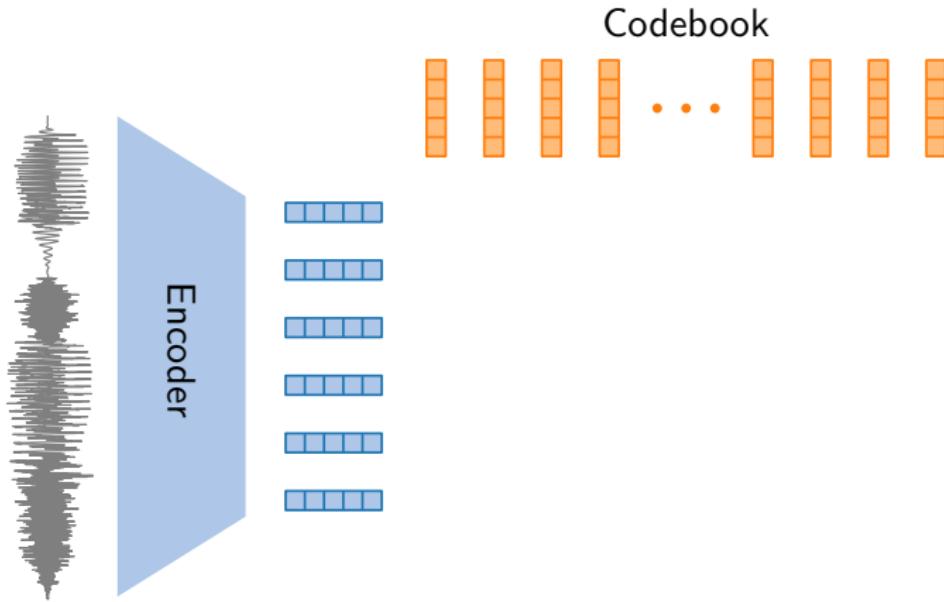


Vector quantisation in neural networks

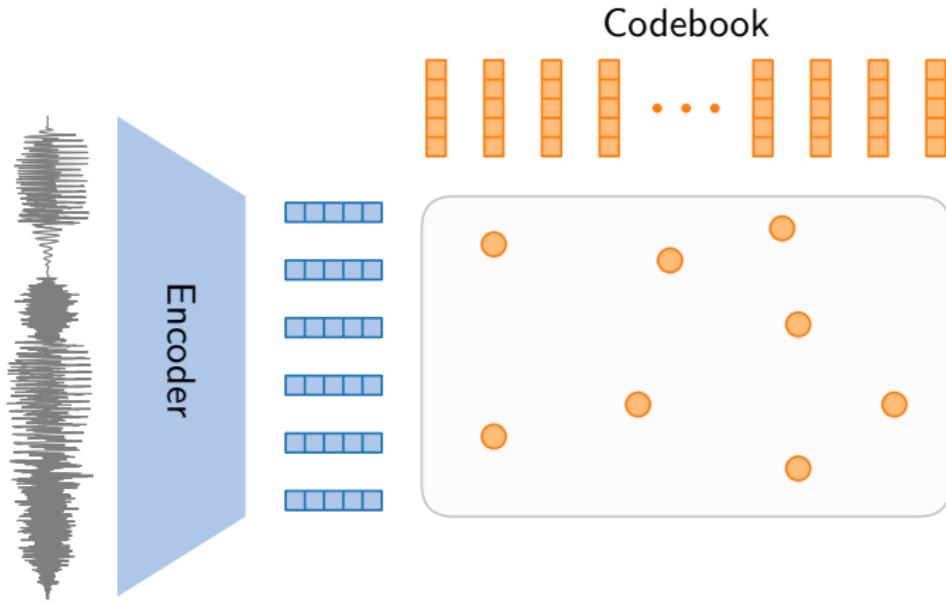
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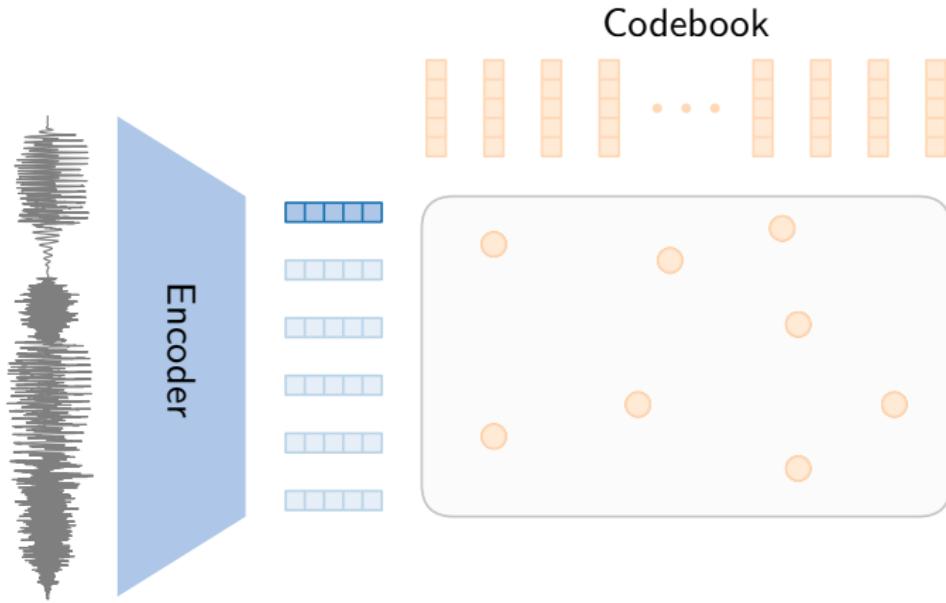
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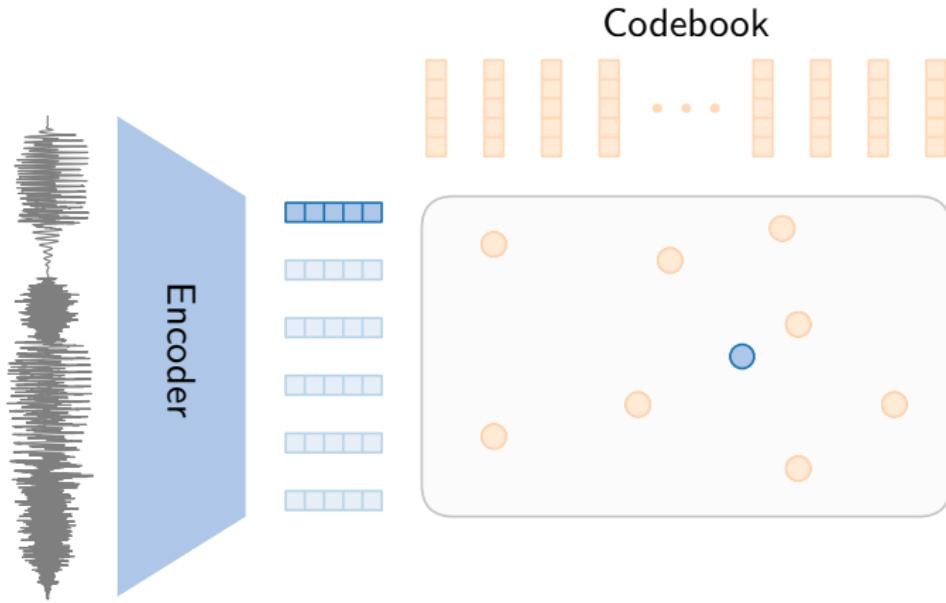
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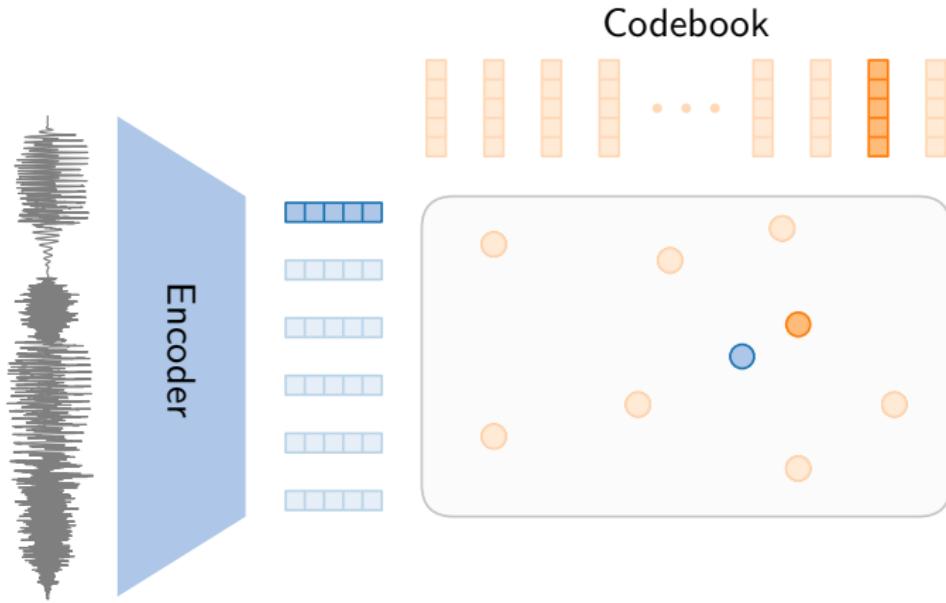
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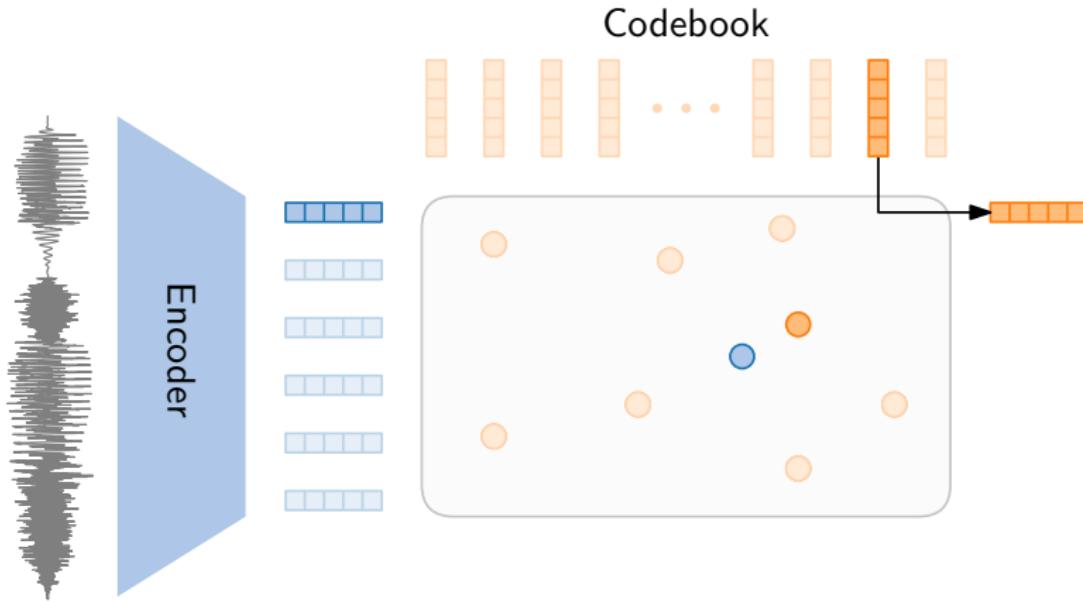
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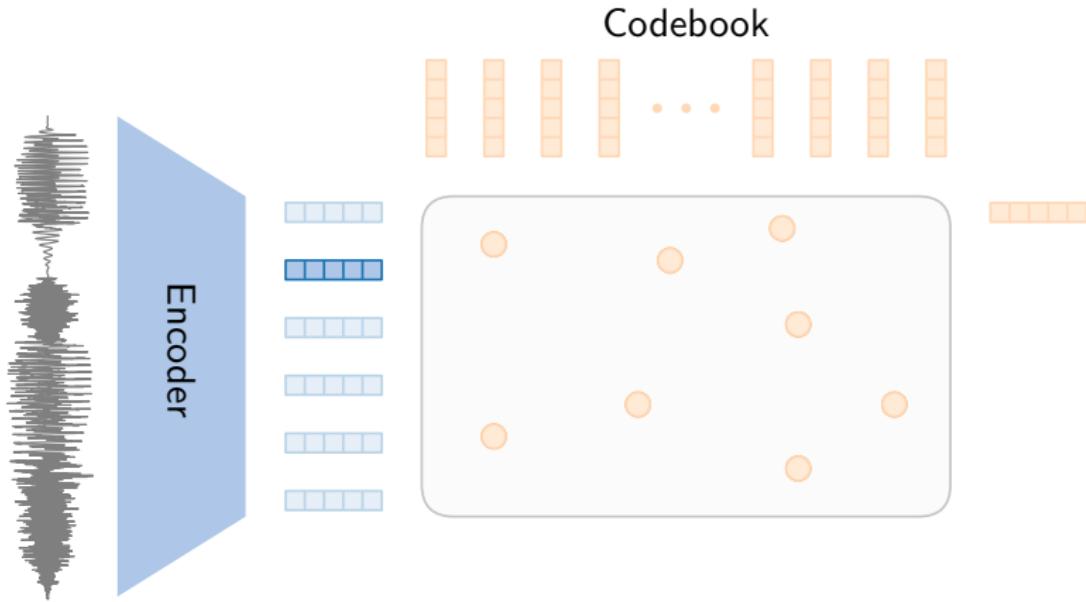
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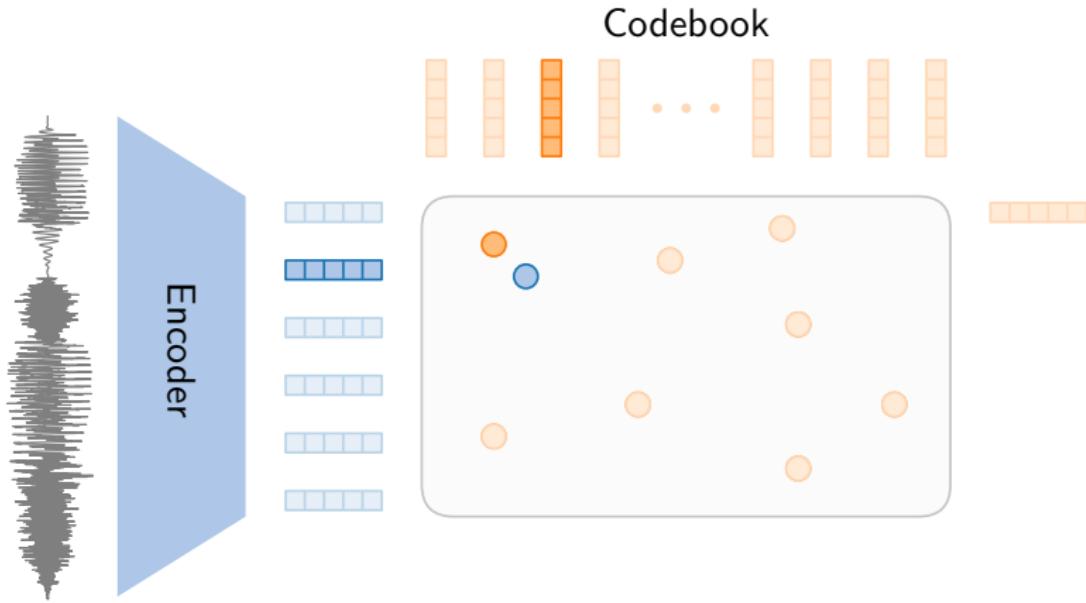
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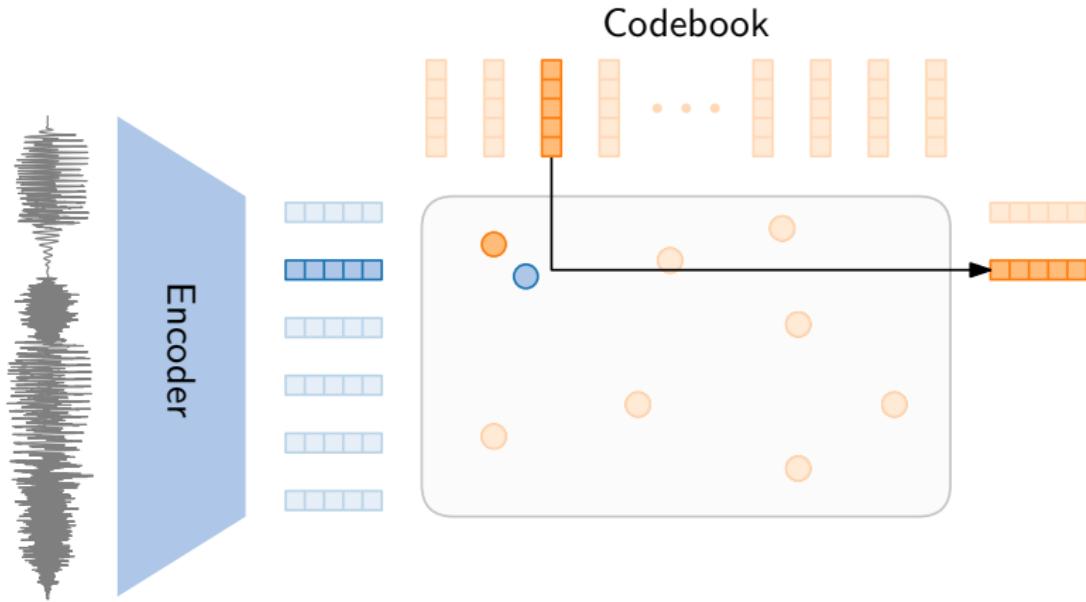
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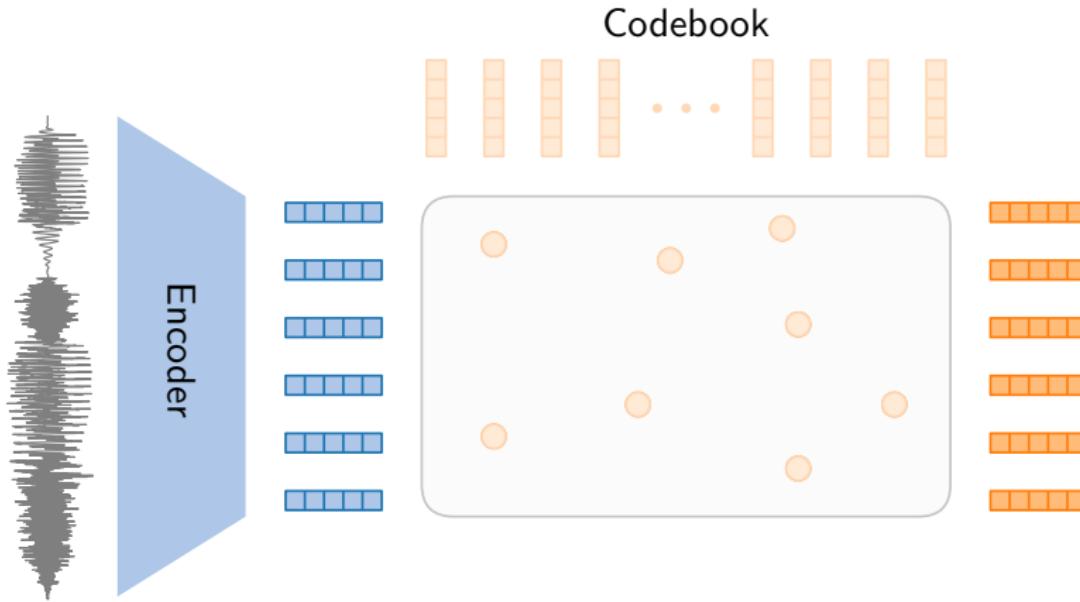
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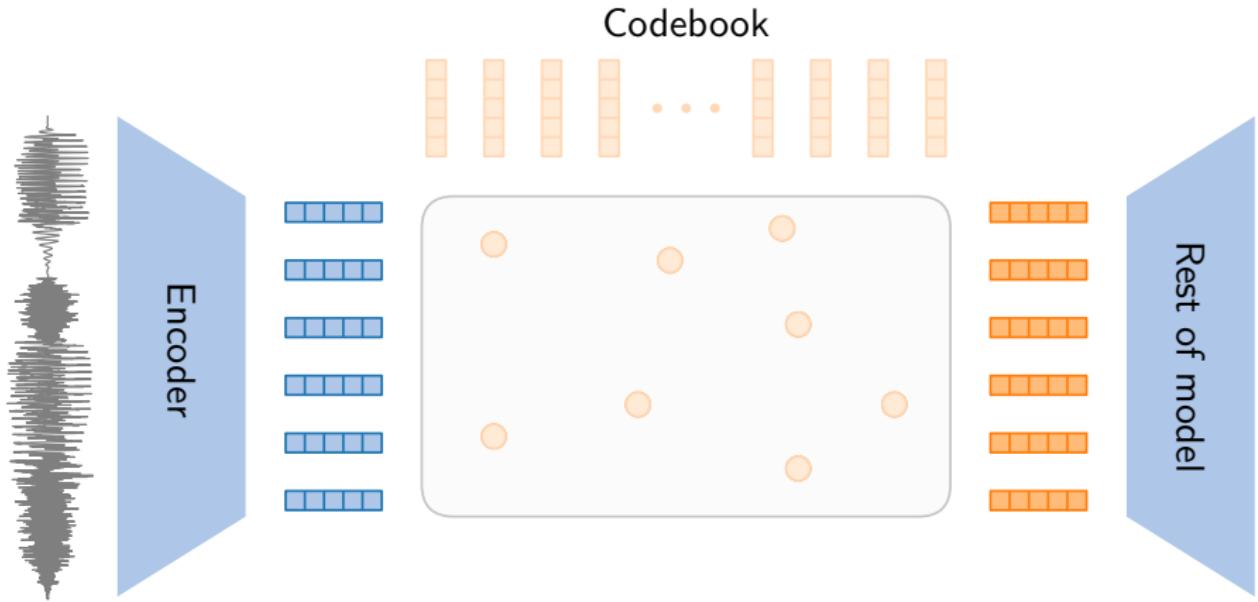
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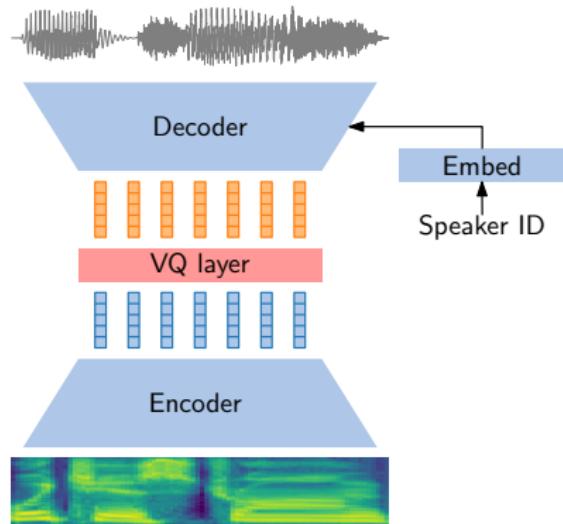


Our contribution

We propose and compare two models for unsupervised acoustic unit discovery:

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VQ-VAE: A vector-quantised variational autoencoder

Inspired by:

Chorowski, et al., "Unsupervised speech representation learning using wavenet autoencoders," *TASLP*, 2019.

Van Niekerk et al., "Vector-quantized neural networks for acoustic unit discovery in the ZeroSpeech 2020 challenge," *Interspeech*, 2020.

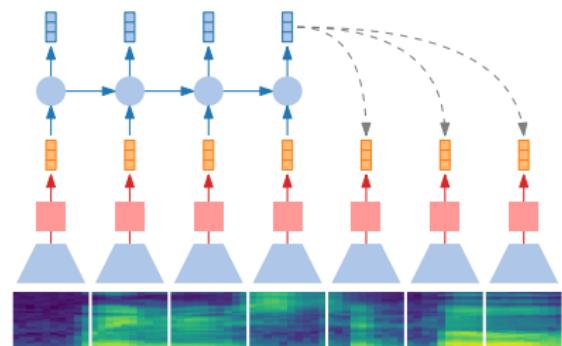
Our contribution

We propose and compare two models for unsupervised acoustic unit discovery:

VQ-CPC: Combining vector quantisation with contrastive predictive coding

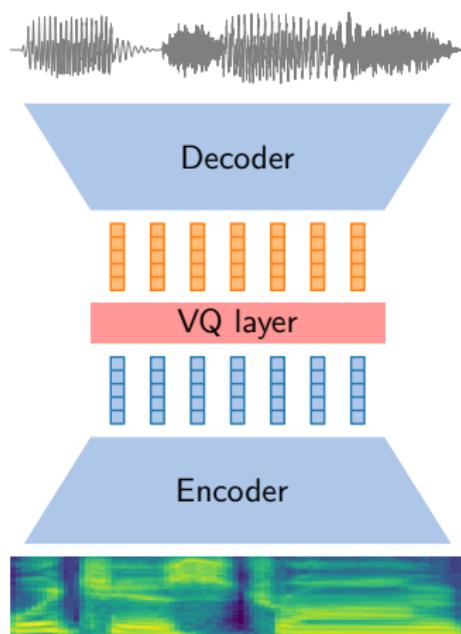
Inspired by:

Van den Oord, et al., "Representation learning with contrastive predictive coding," *arXiv*, 2018.

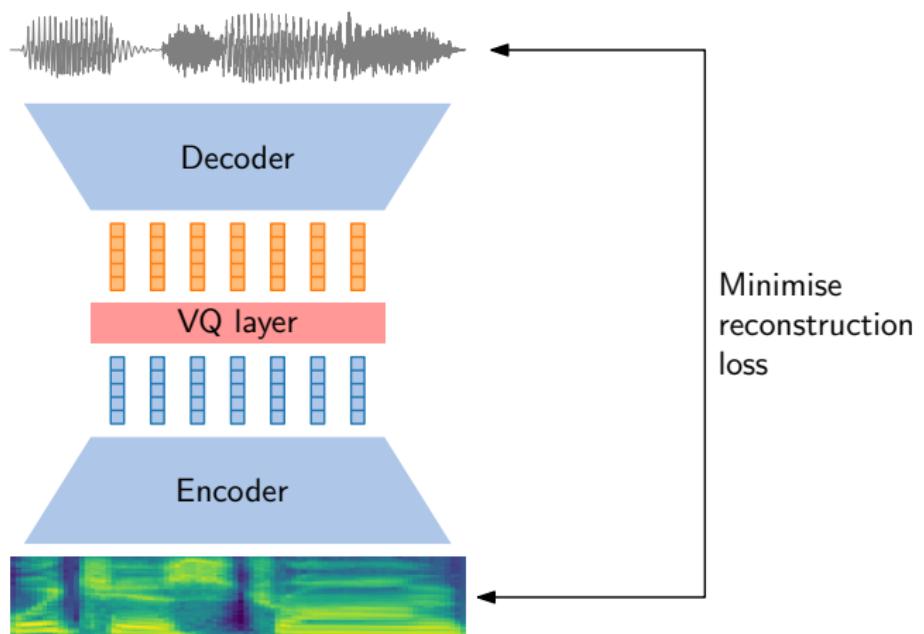


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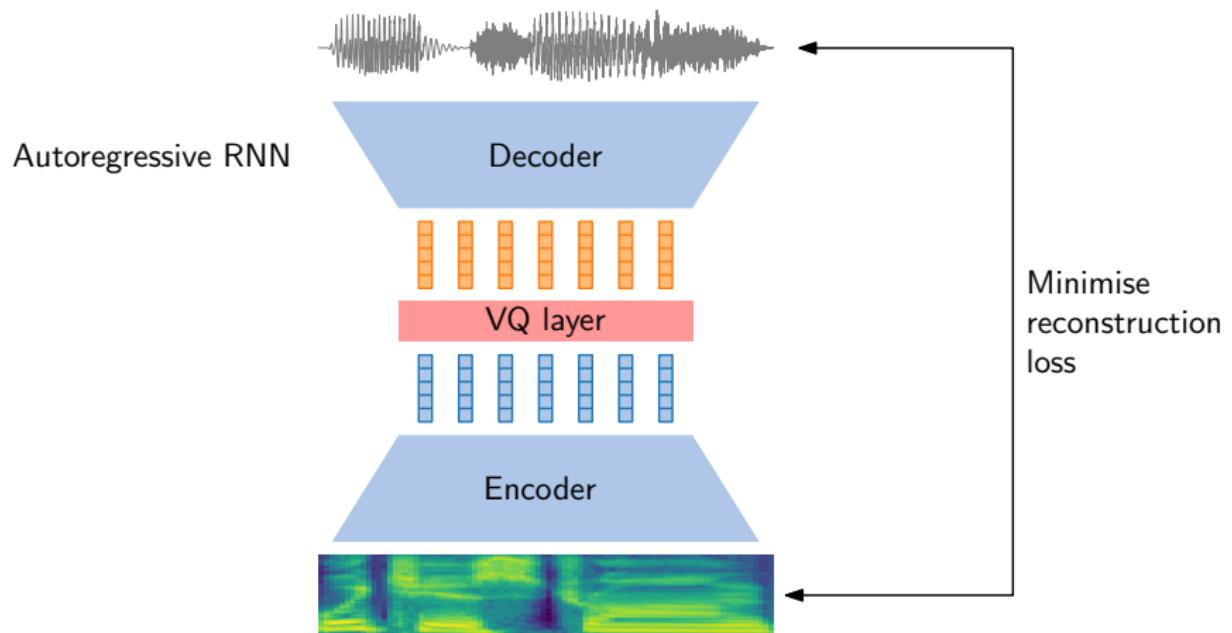
Vector-quantised variational autoencoder



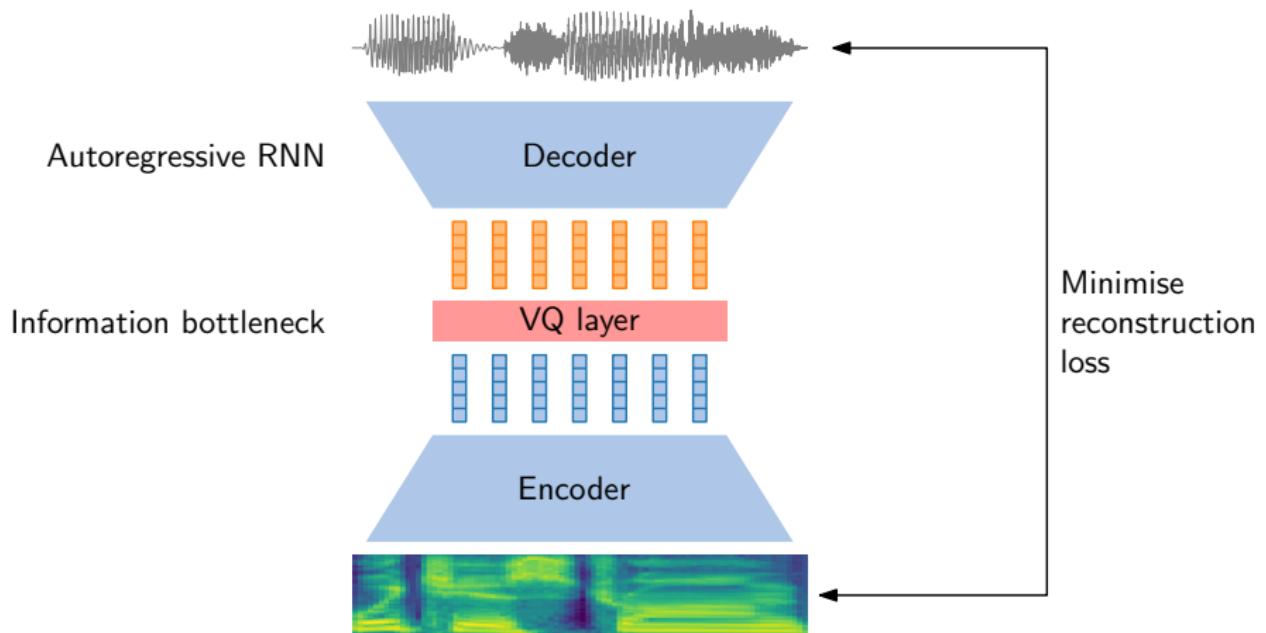
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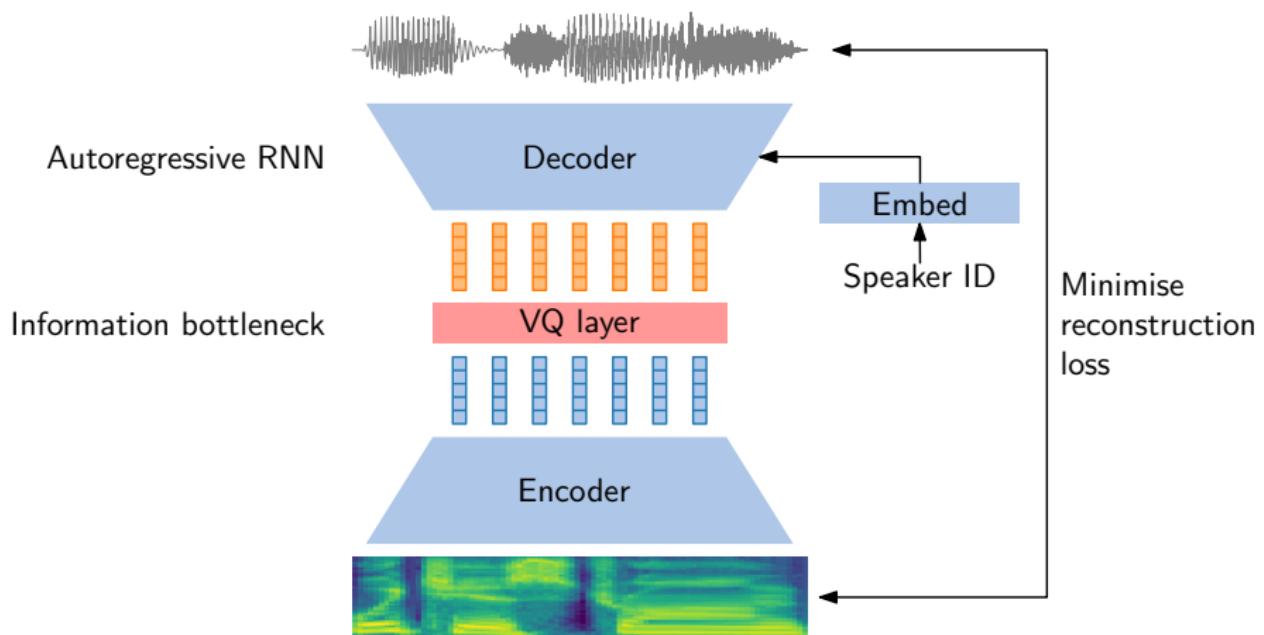
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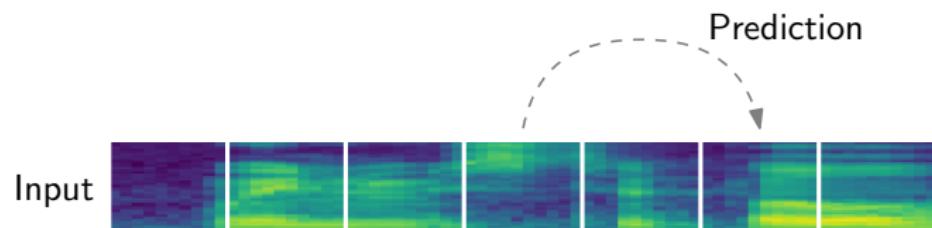
Vector-quantised variational autoencoder



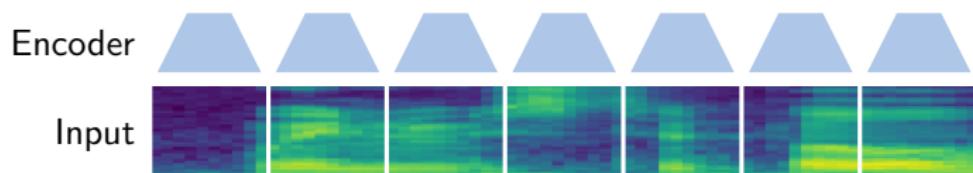
Vector-quantised variational autoencoder



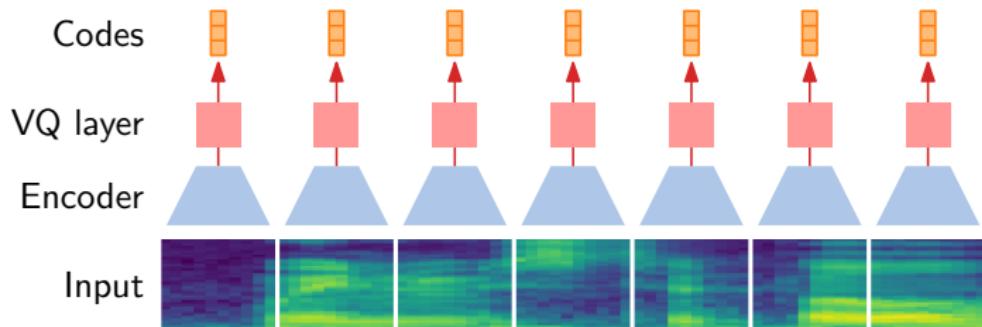
Vector-quantised contrastive predictive coding



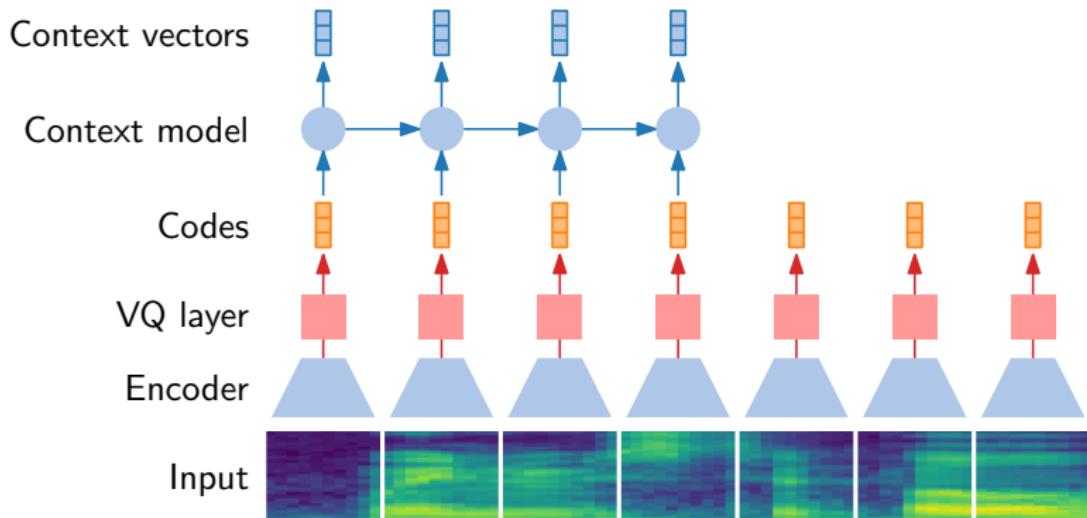
Vector-quantised contrastive predictive coding



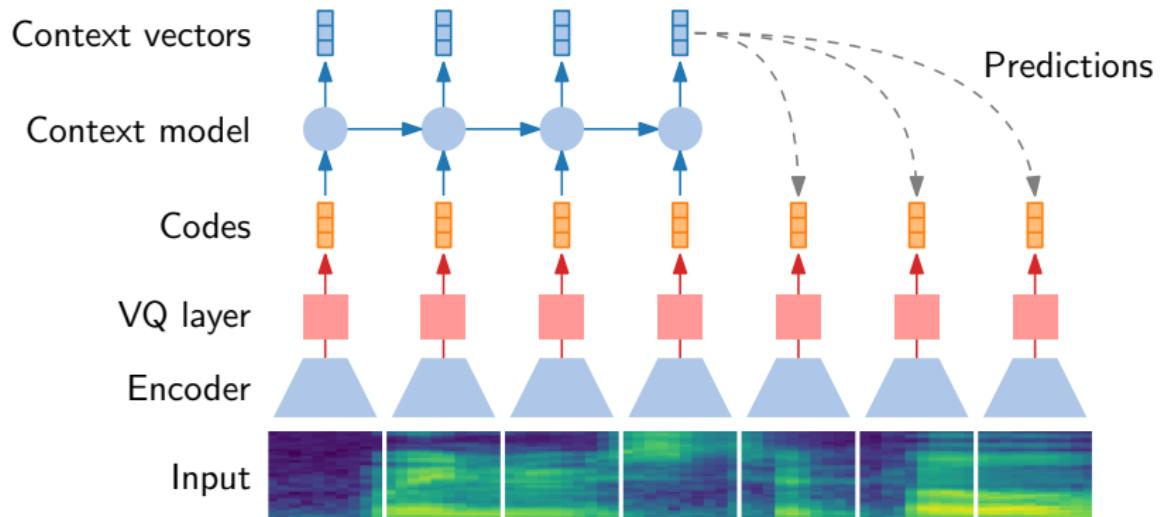
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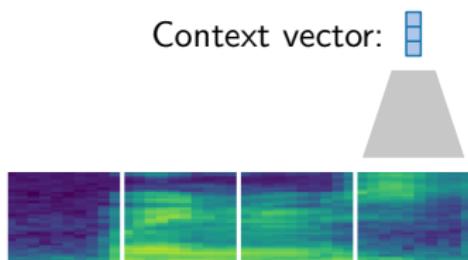
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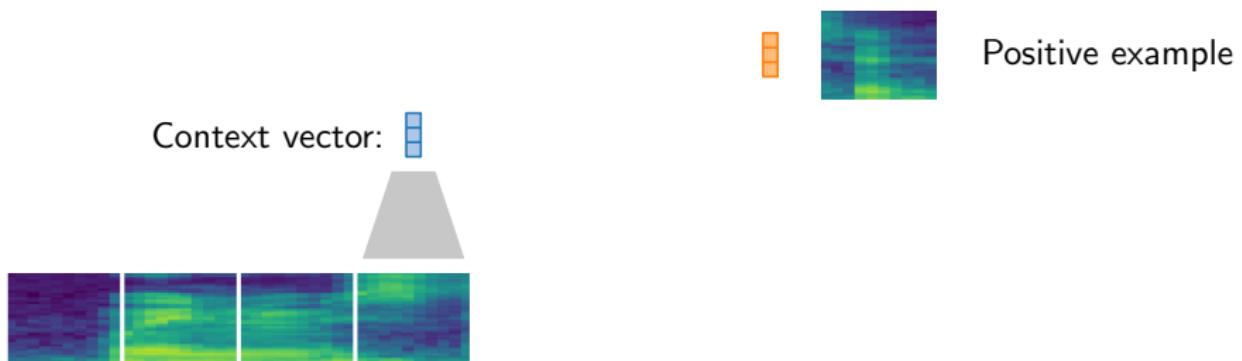
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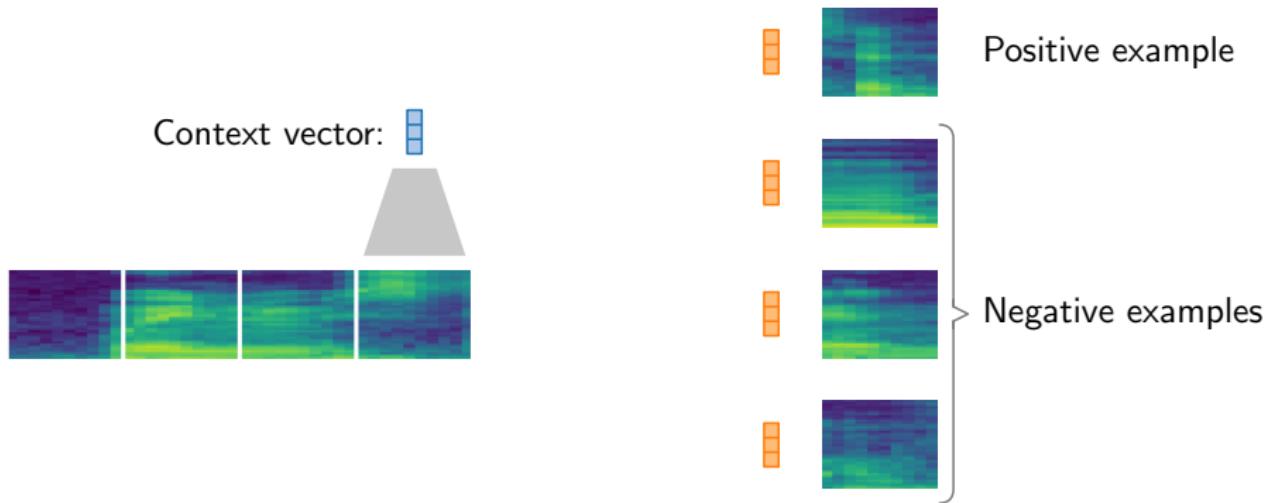
Vector-quantised contrastive predictive coding



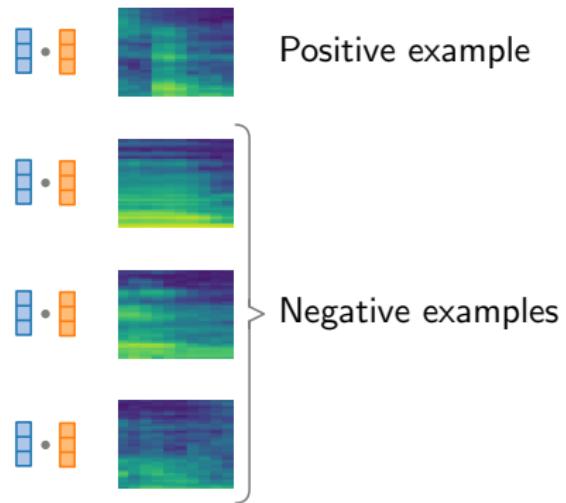
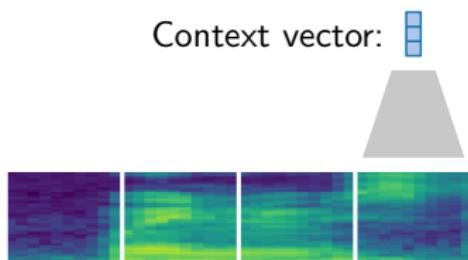
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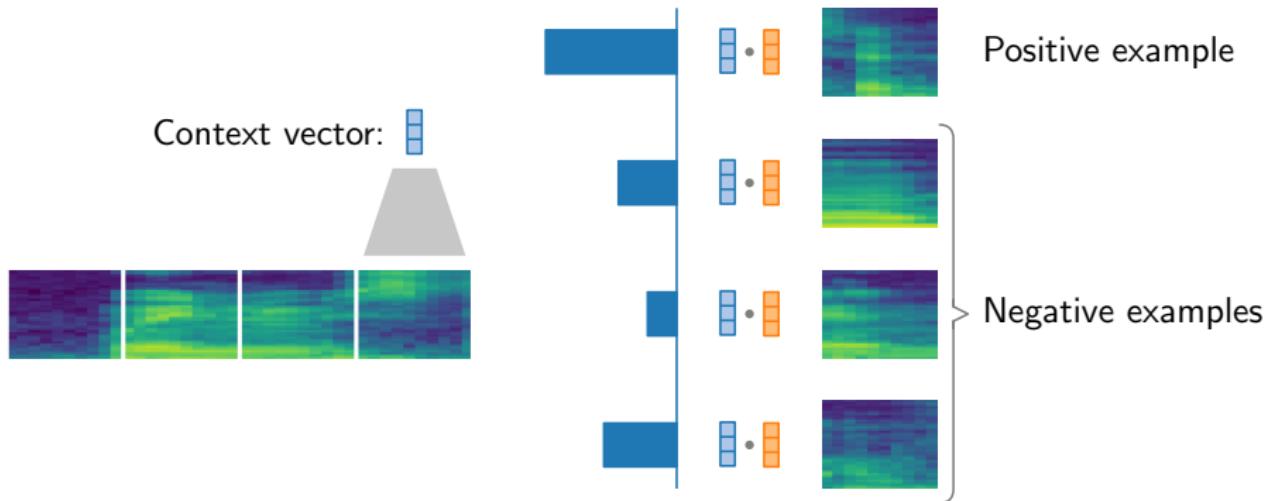
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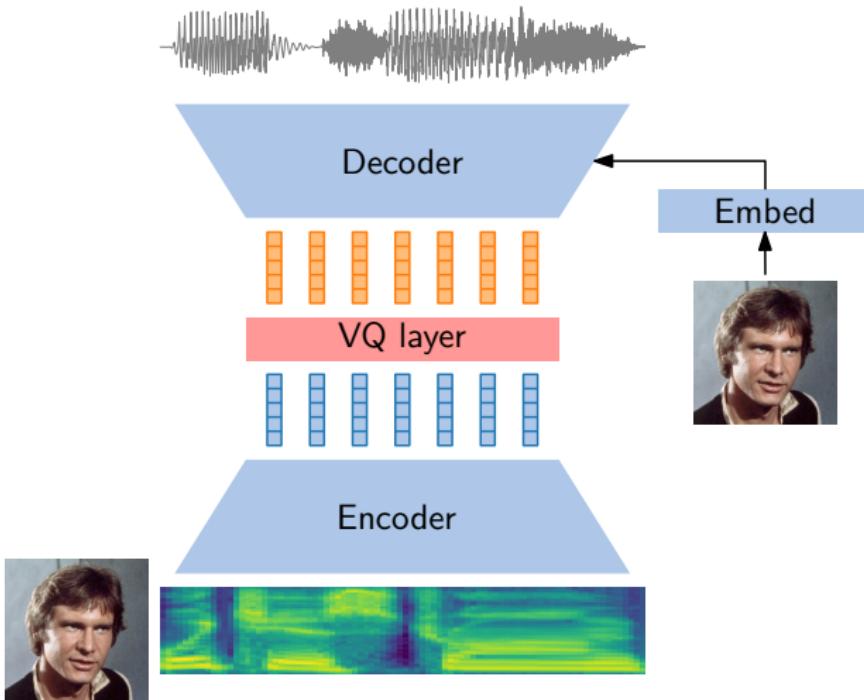
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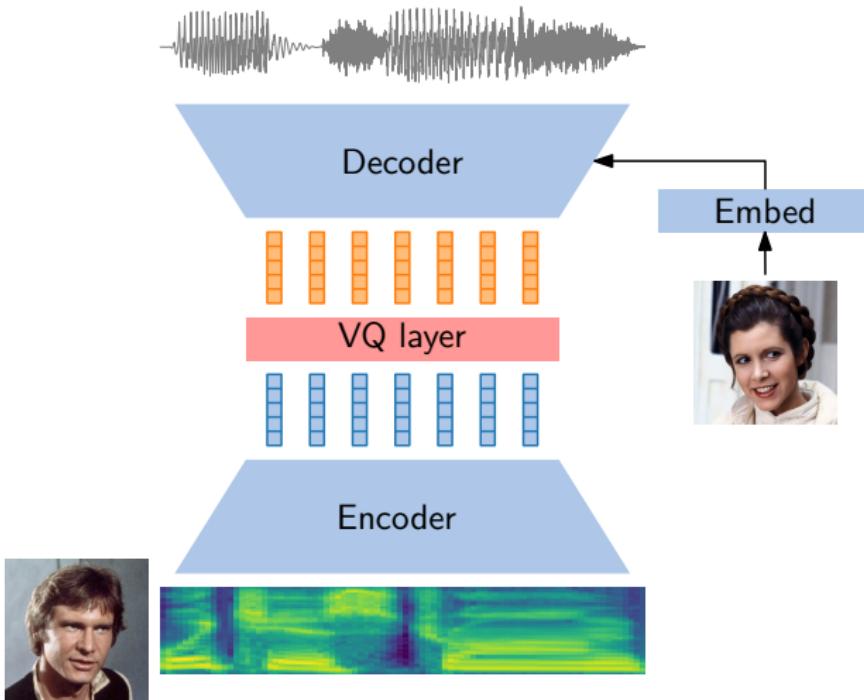
Vector-quantised contrastive predictive coding



Evaluation: Voice conversion



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Example conversions

Example 1:

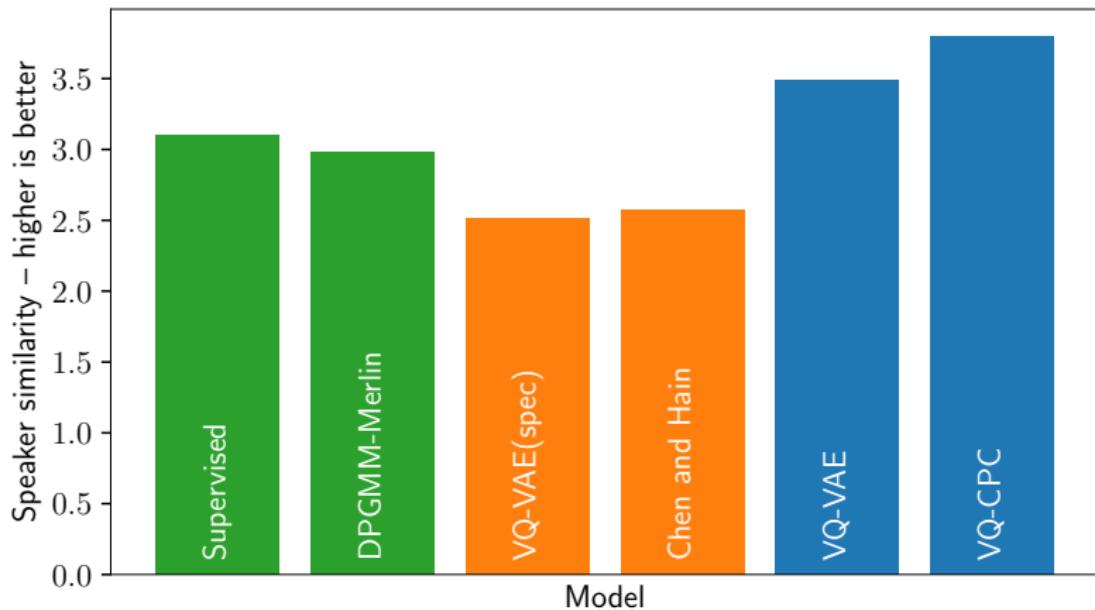
- Source: [Play](#)
- Converted: [Play](#)
- Target: [Play](#)

Example 2:

- Source: [Play](#)
- Converted: [Play](#)
- Target: [Play](#)

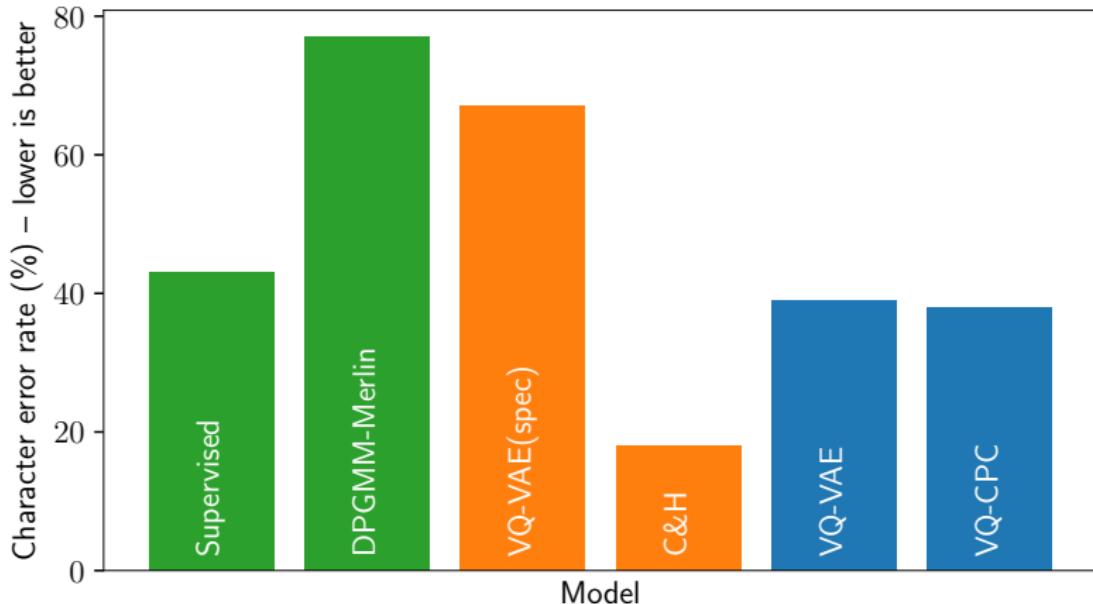
Evaluation: Speaker similarity

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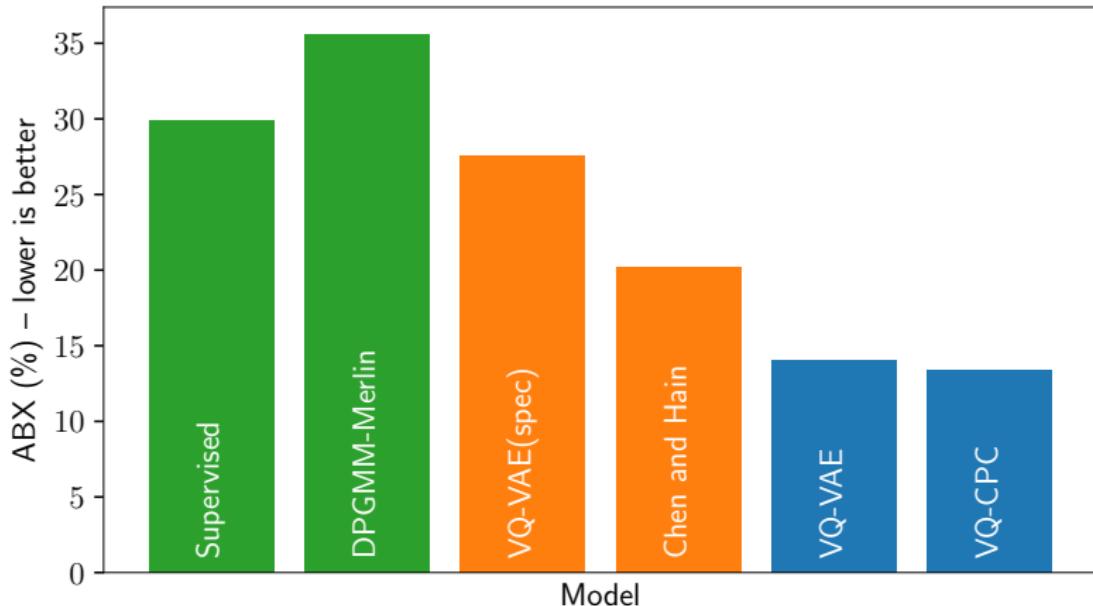


Chen and Hain, "Unsupervised acoustic unit representation learning for voice conversion using WaveNet auto-encoders," *Interspeech*, 2020.

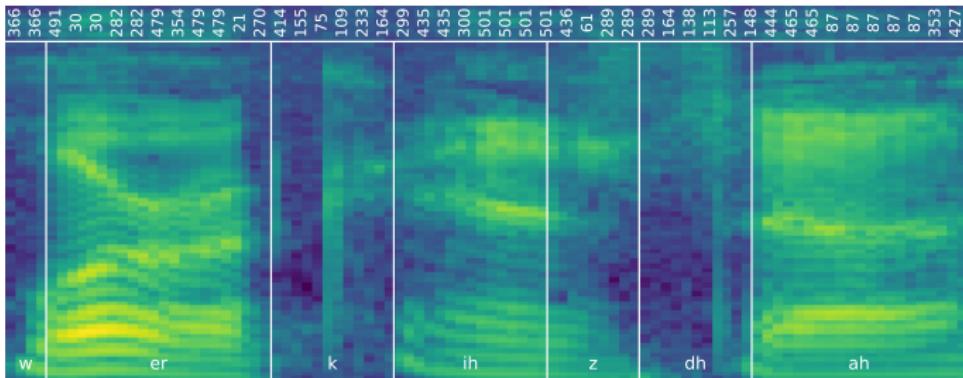
Evaluation: Intelligibility



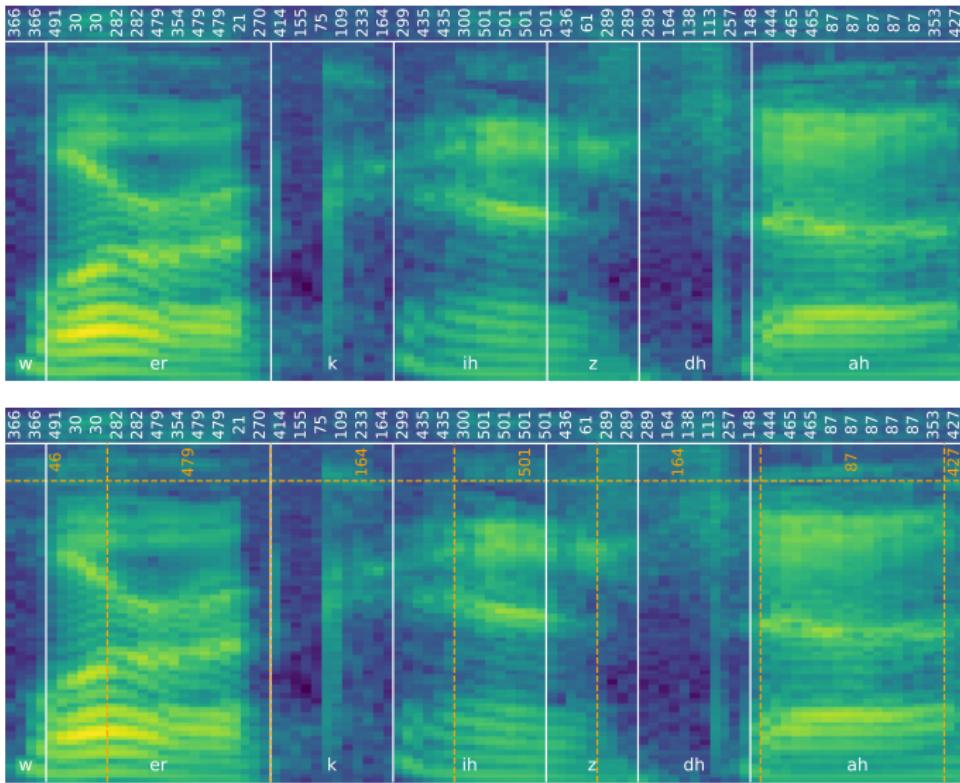
Evaluation: ABX phone discrimination



VQ-CPC codes



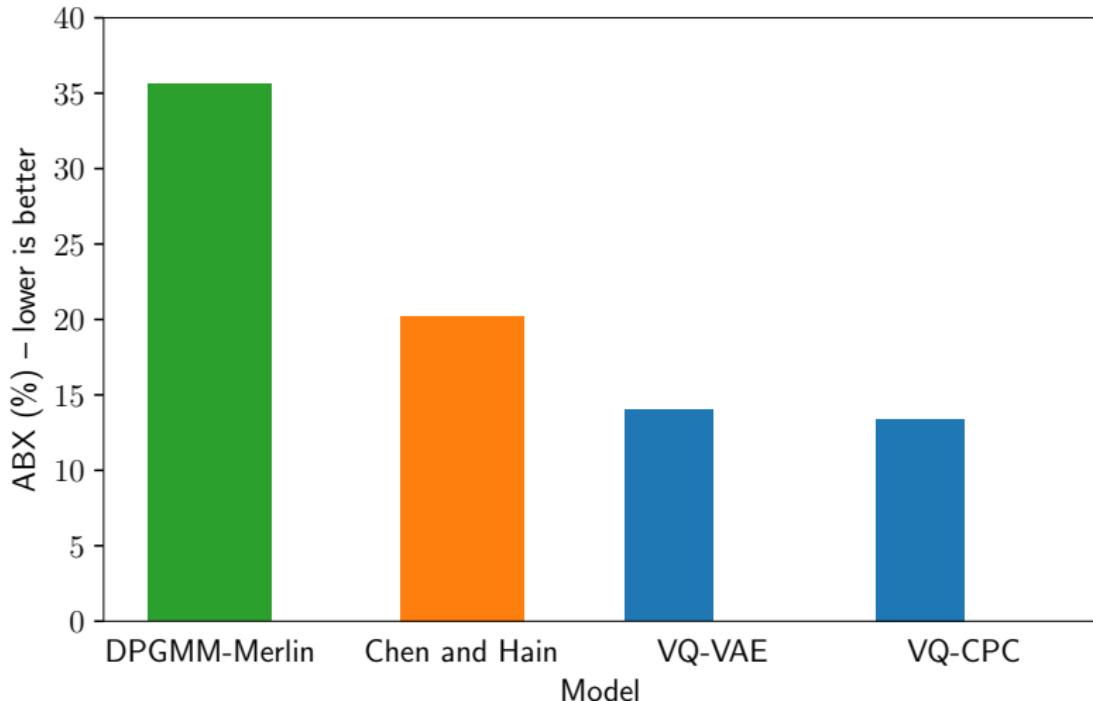
VQ-CPC codes



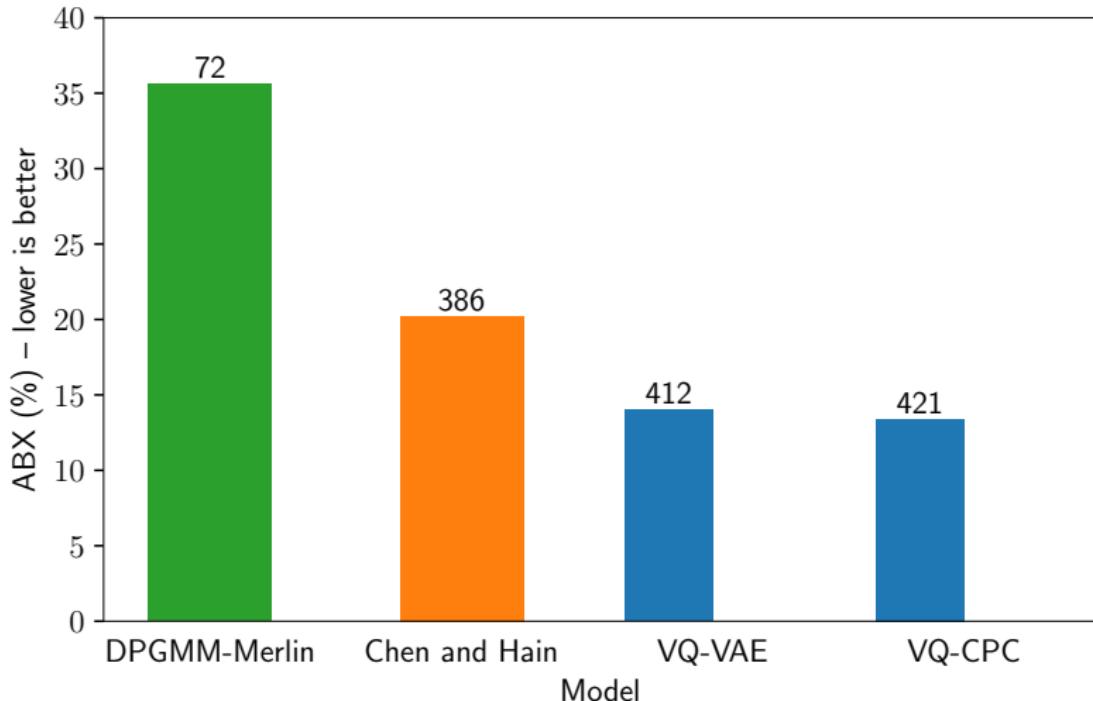
Inspired by:

Chorowski et al., "Unsupervised neural segmentation and clustering for unit discovery in sequential data," PGR Workshop, 2019.

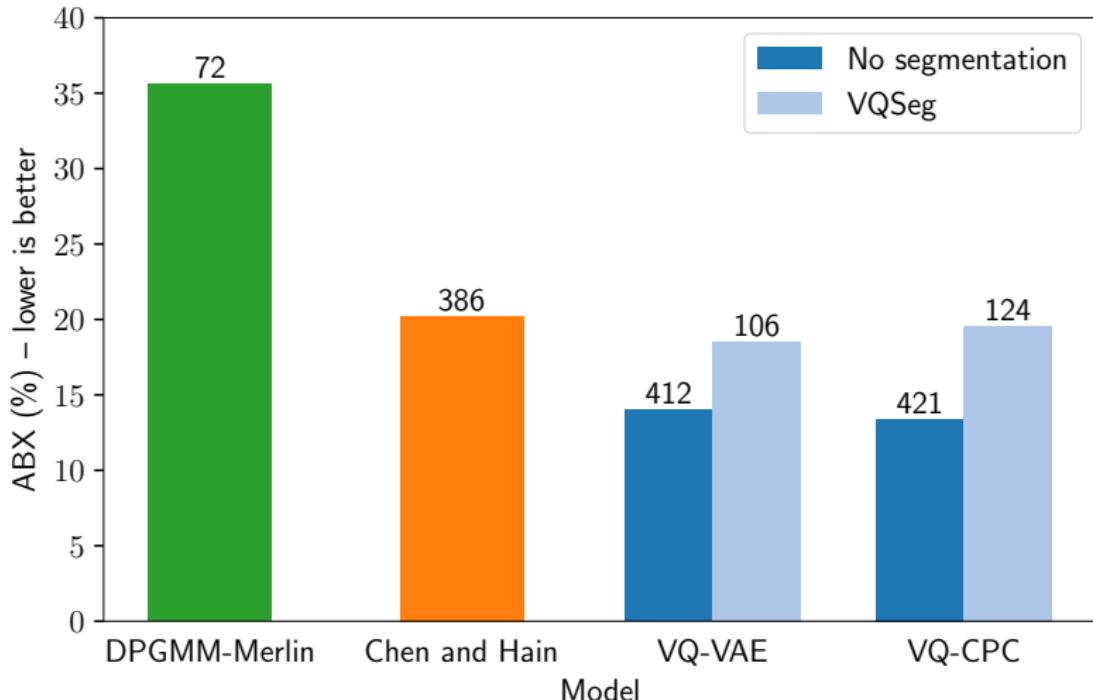
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2. Multimodal few-shot learning from images and speech

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Eloff



Herman
Engelbrecht



Leanne
Nortje

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Ryan
Eloff



Herman
Engelbrecht



Leanne
Nortje

Nortje and Kamper, "Unsupervised vs. transfer learning for multimodal one-shot matching of speech and images," *Interspeech*, 2020.



TOYOTA
HSR 104
preferred Networks















A



B



C

?



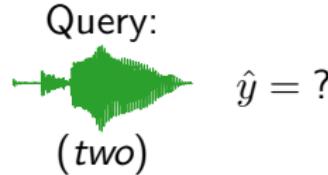
Unimodal one-shot learning and classification



Fei-Fei et al., "One-shot learning of object categories," *TPAMI*, 2006.

Lake et al., "One-shot learning of generative speech concepts," *CogSci*, 2014.

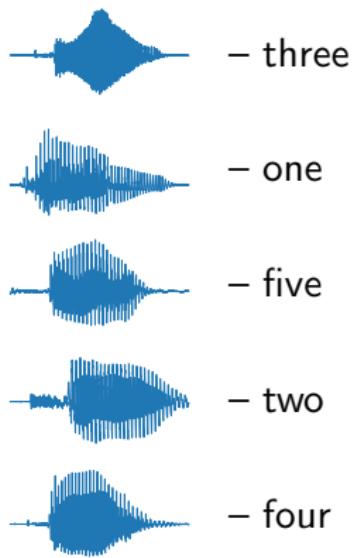
Unimodal one-shot learning and classification



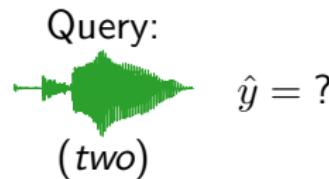
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Unimodal one-shot learning and classification



One-shot speech learning

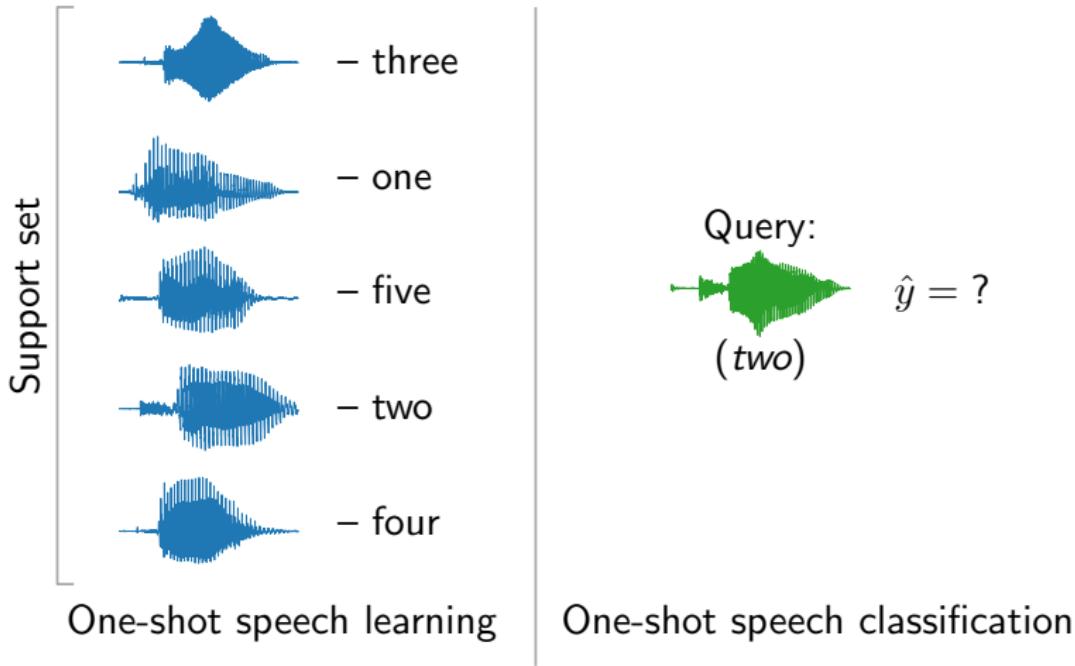


One-shot speech classification

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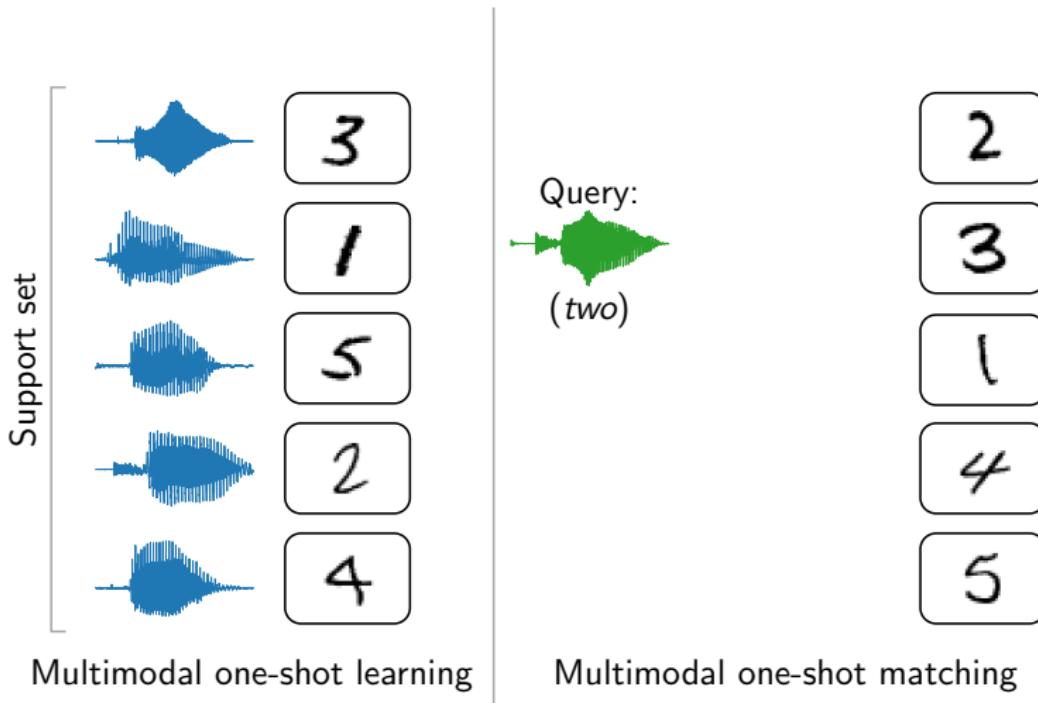
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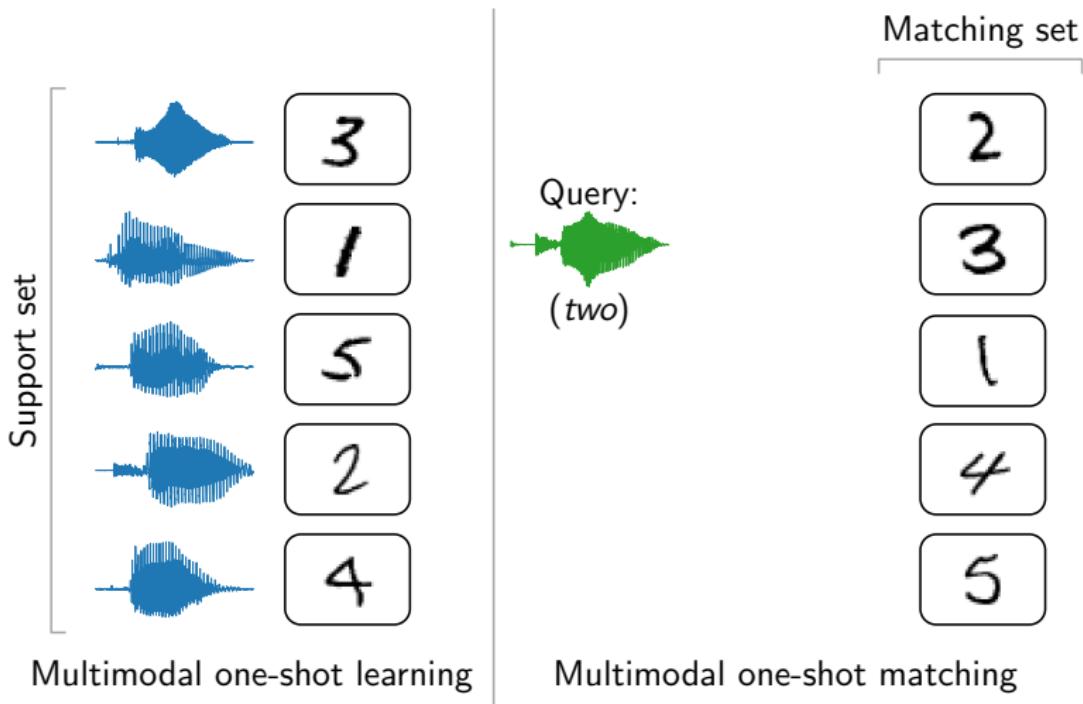
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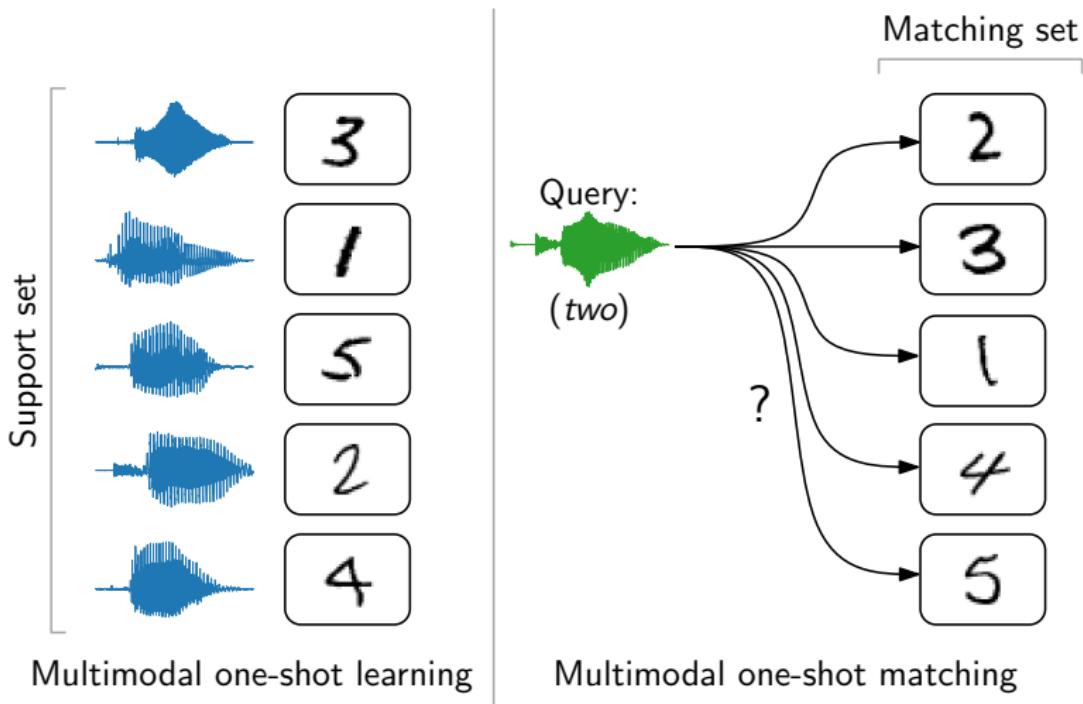
Multimodal one-shot learning and matching



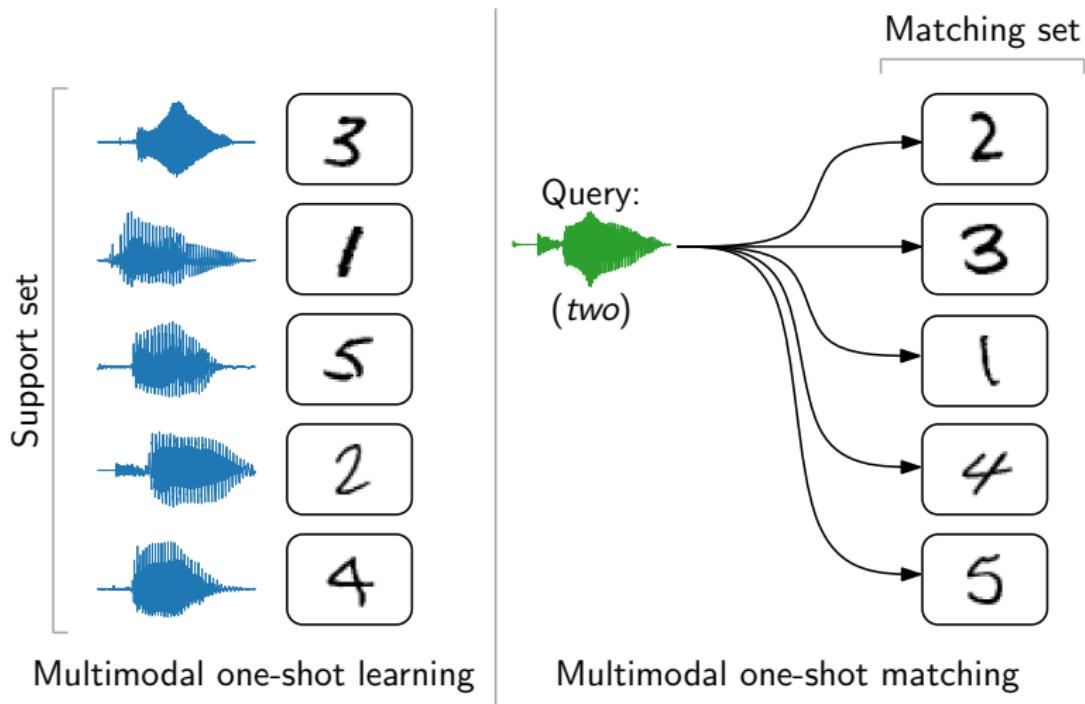
Multimodal one-shot learning and matching



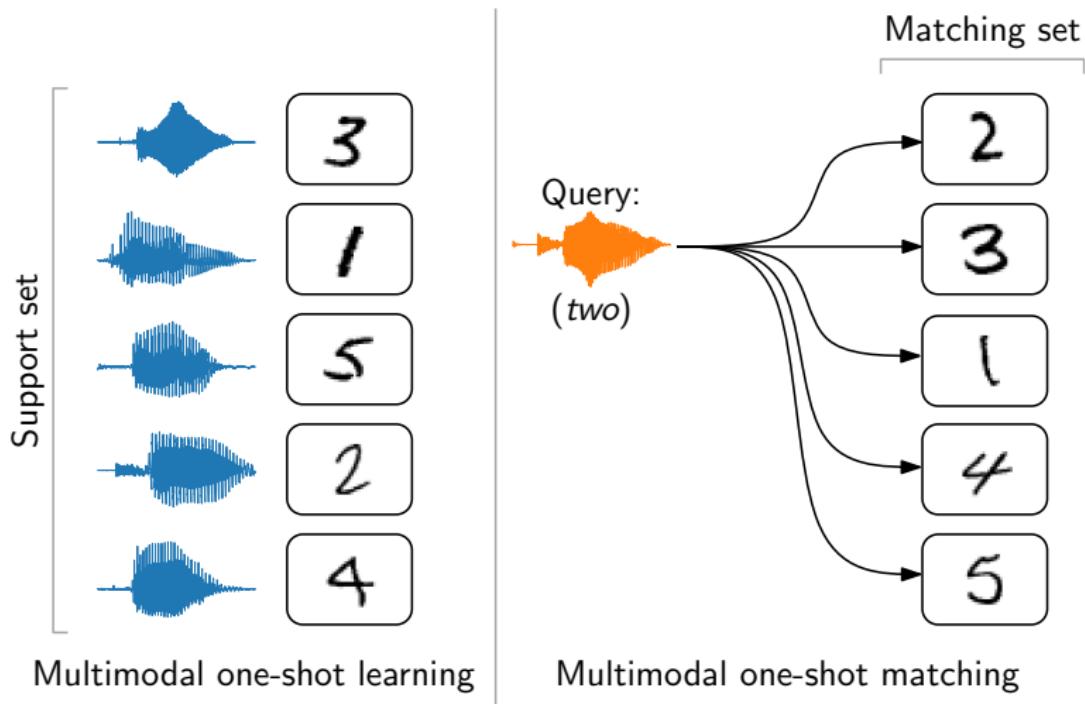
Multimodal one-shot learning and matching



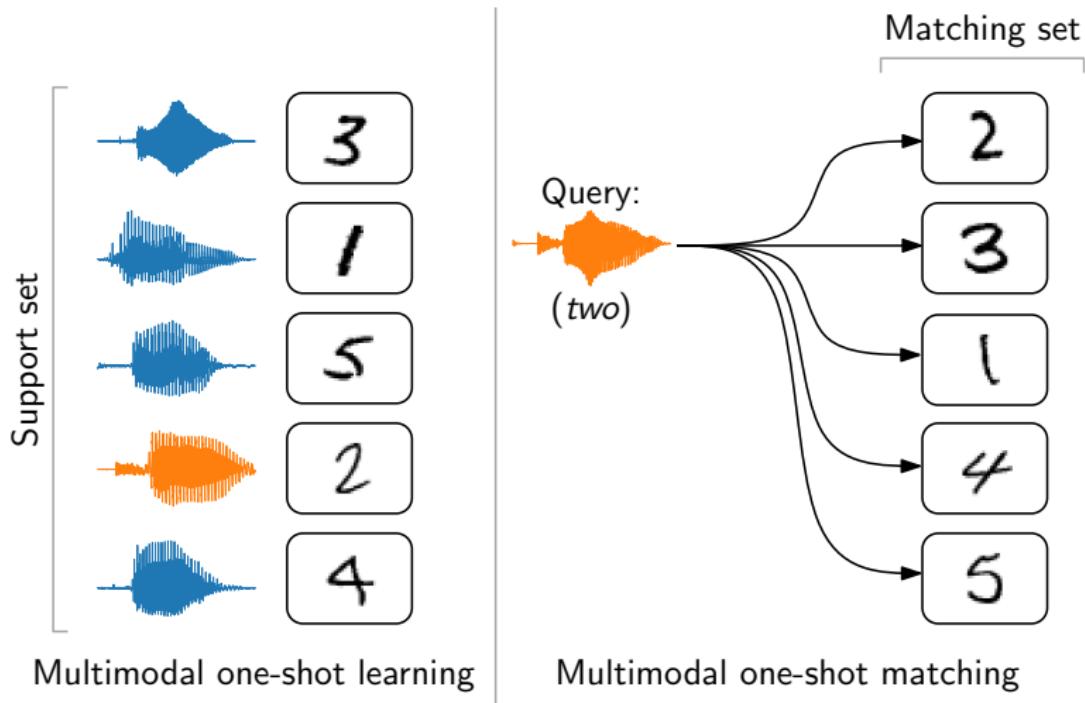
Two-step (indirect) multimodal one-shot approach



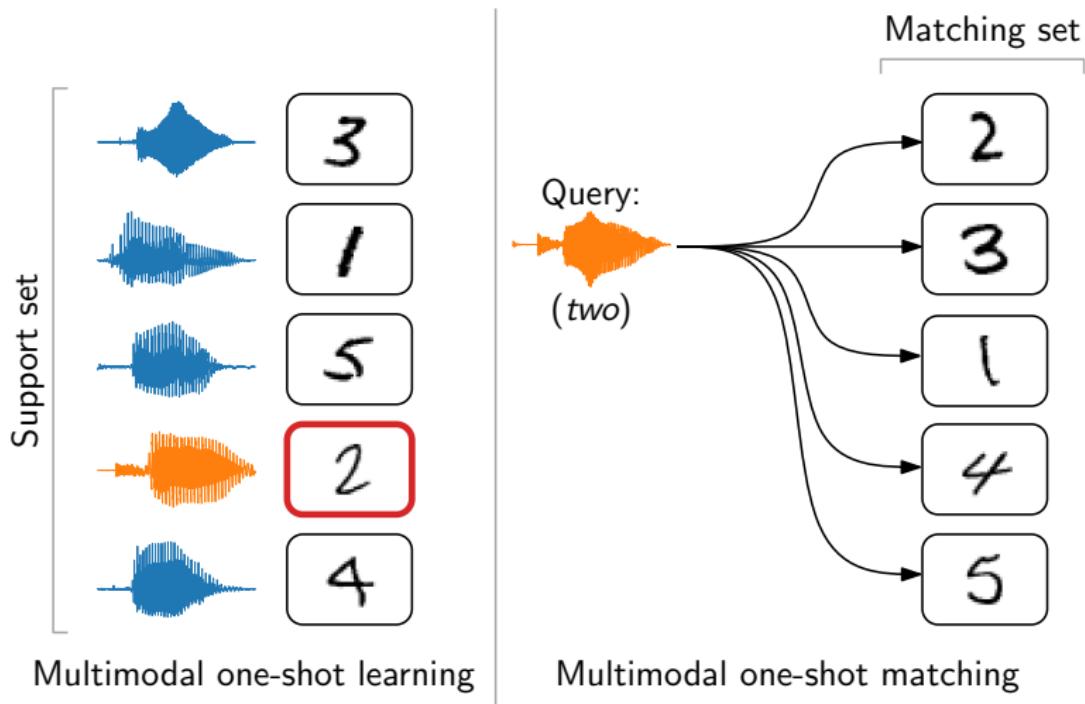
Two-step (indirect) multimodal one-shot approach



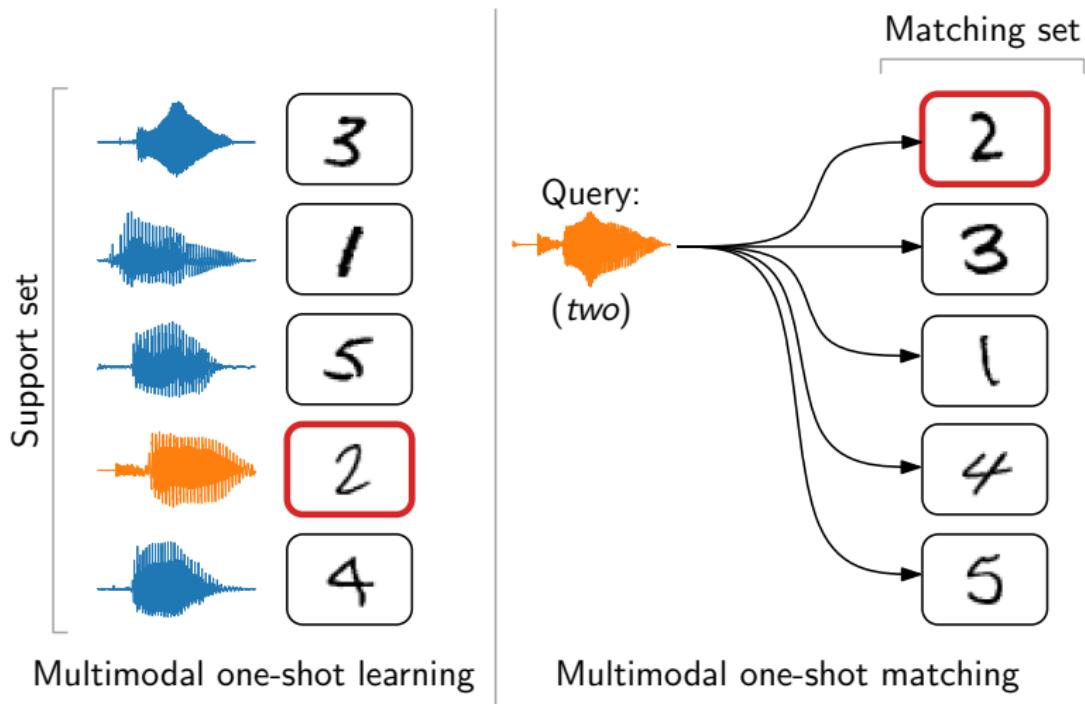
Two-step (indirect) multimodal one-shot approach



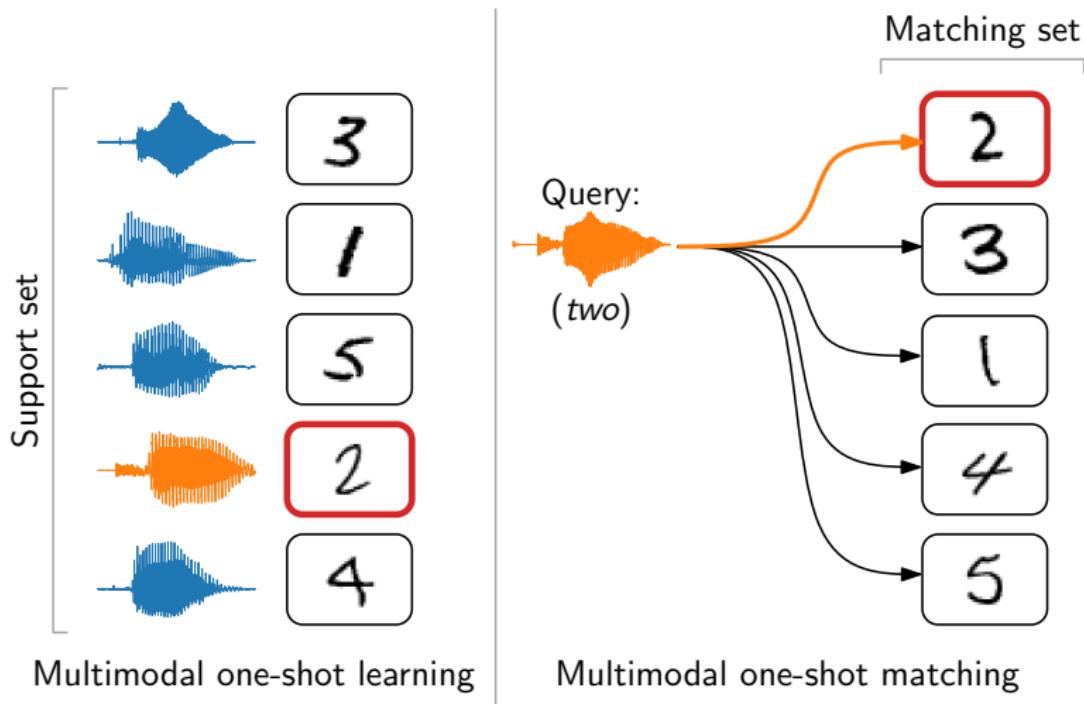
Two-step (indirect) multimodal one-shot approach



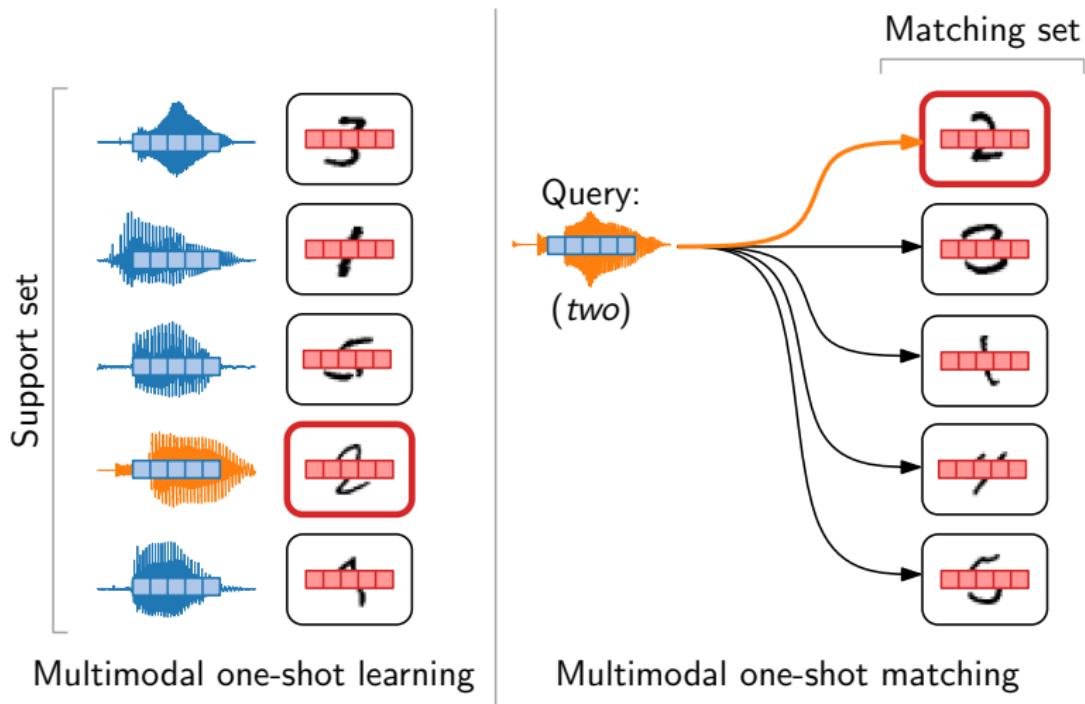
Two-step (indirect) multimodal one-shot approach



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Two-step (indirect) multimodal one-shot approach



Two-step (indirect) multimodal one-shot approach

- Requires within-modality speech-to-speech and image-to-image distance metrics
- Baseline: DTW over speech, cosine over image pixels
- Or representations/distance metrics can be **learned**

Two-step (indirect) multimodal one-shot approach

- Requires within-modality speech-to-speech and image-to-image distance metrics
- Baseline: DTW over speech, cosine over image pixels
- Or representations/distance metrics can be **learned**
- Compare two learning methodologies on TIDigits (speech) paired with MNIST (images)

Nortje and Kamper, "Unsupervised vs. transfer learning for multimodal one-shot matching of speech and images," *Interspeech*, 2020.

1. Transfer learning from labelled background data

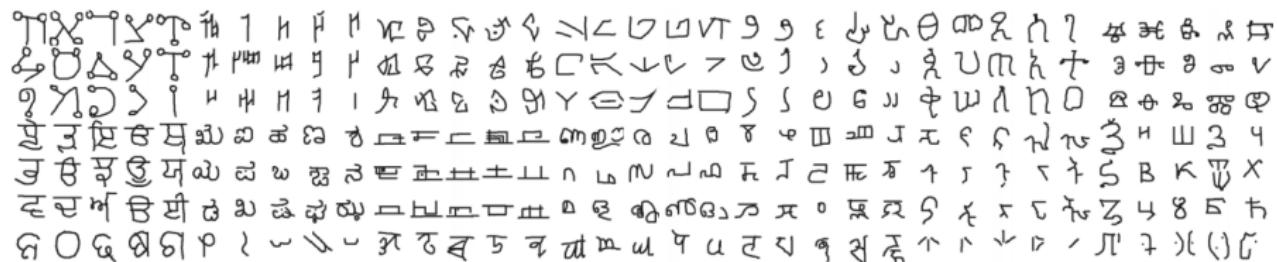
1. Transfer learning from labelled background data

Omniglot (no digits):

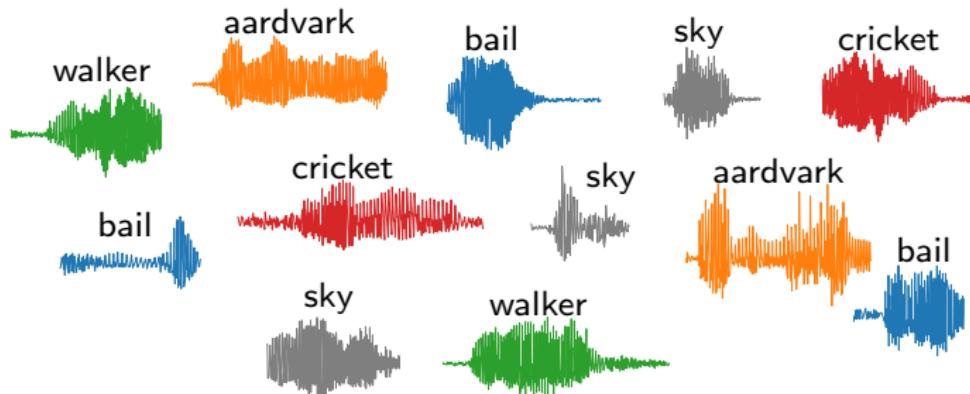
፳፻፲፭ የፌዴራል ተስፋዣ ስርዓት አንቀጽ ፩፭፭ ዓ.ም. የፌዴራል ተስፋዣ ስርዓት አንቀጽ ፩፭፭ ዓ.ም. የፌዴራል ተስፋዣ ስርዓት አንቀጽ ፩፭፭ ዓ.ም.

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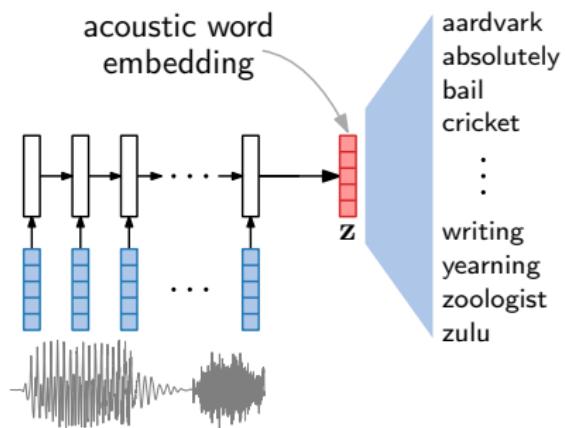
Omniglot (no digits):



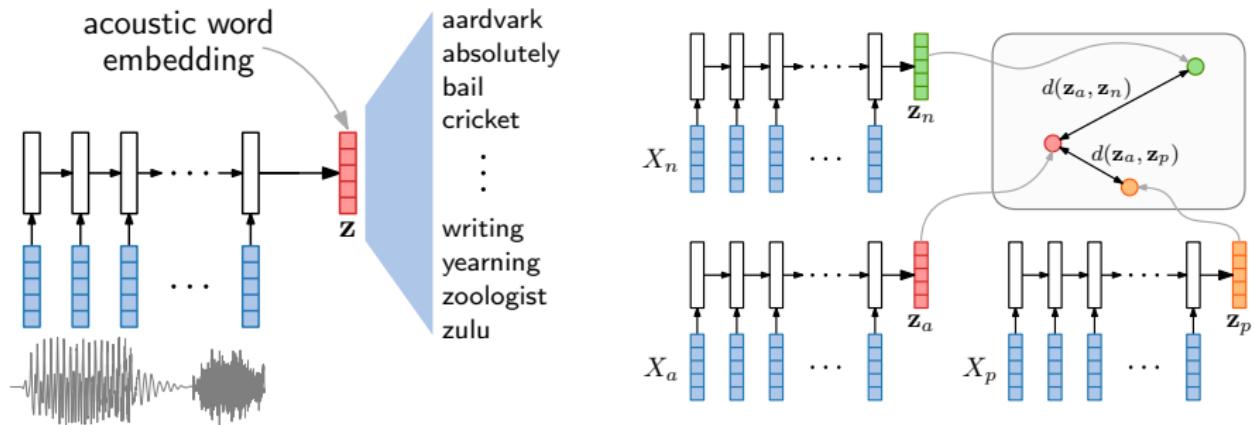
Isolated labelled words (no digits):



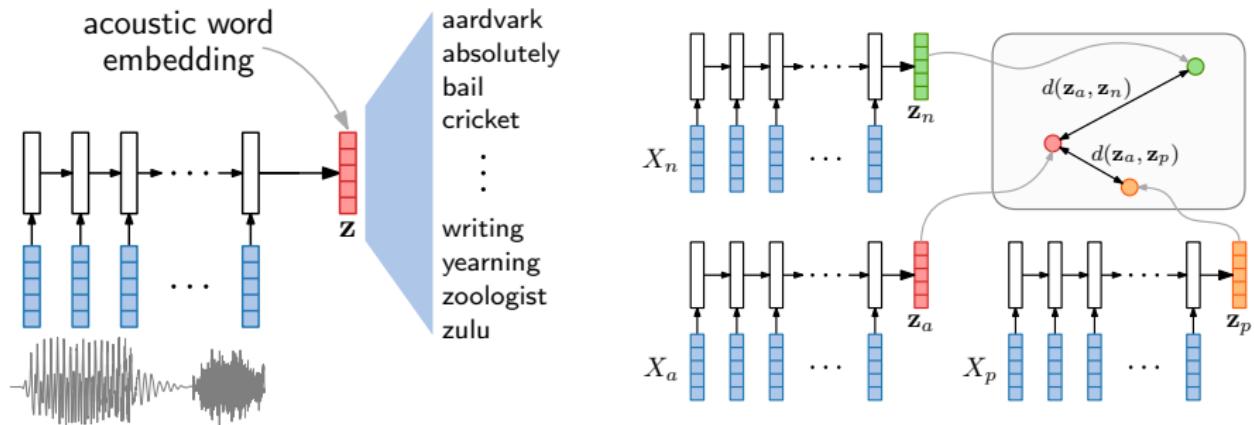
1. Supervised models for transfer learning



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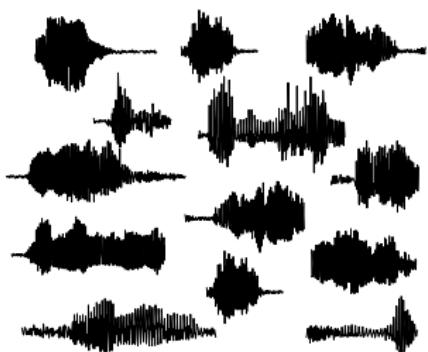


1. Supervised models for transfer learning

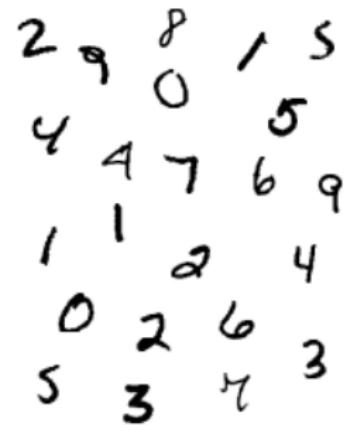


2. Unsupervised learning from unlabelled in-domain data

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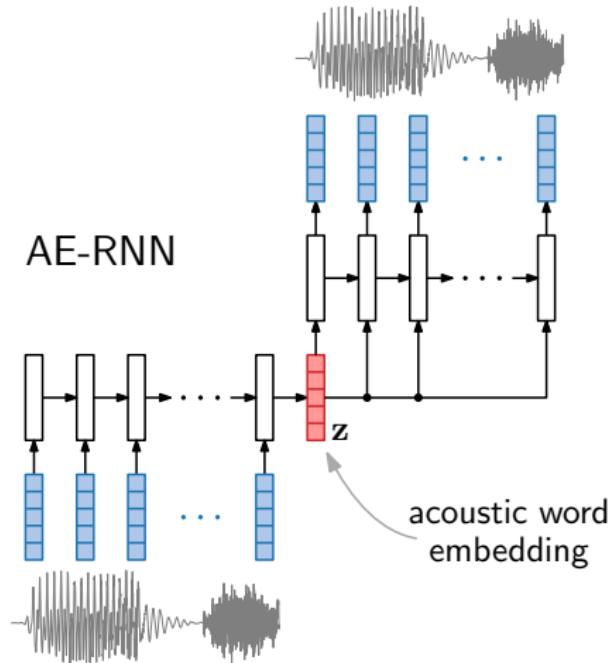


Unlabelled speech



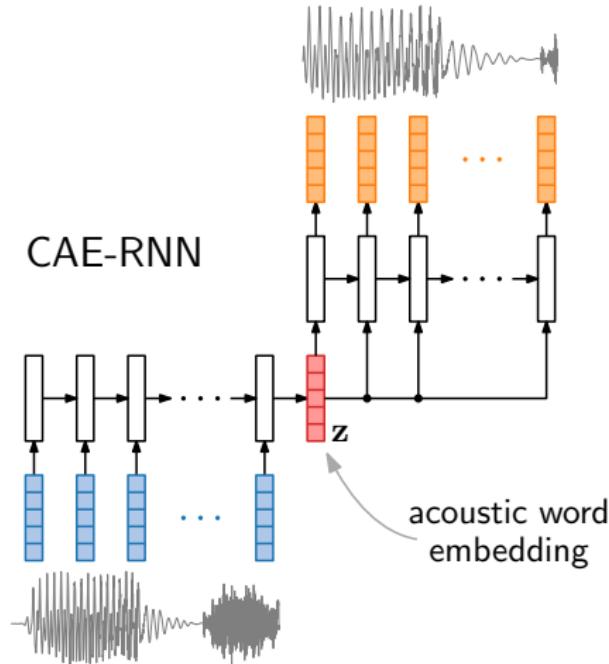
Unlabelled images

2. Unsupervised models



Chung et al., "Unsupervised learning of audio segment representations using sequence-to-sequence recurrent neural networks," *Interspeech*, 2016.

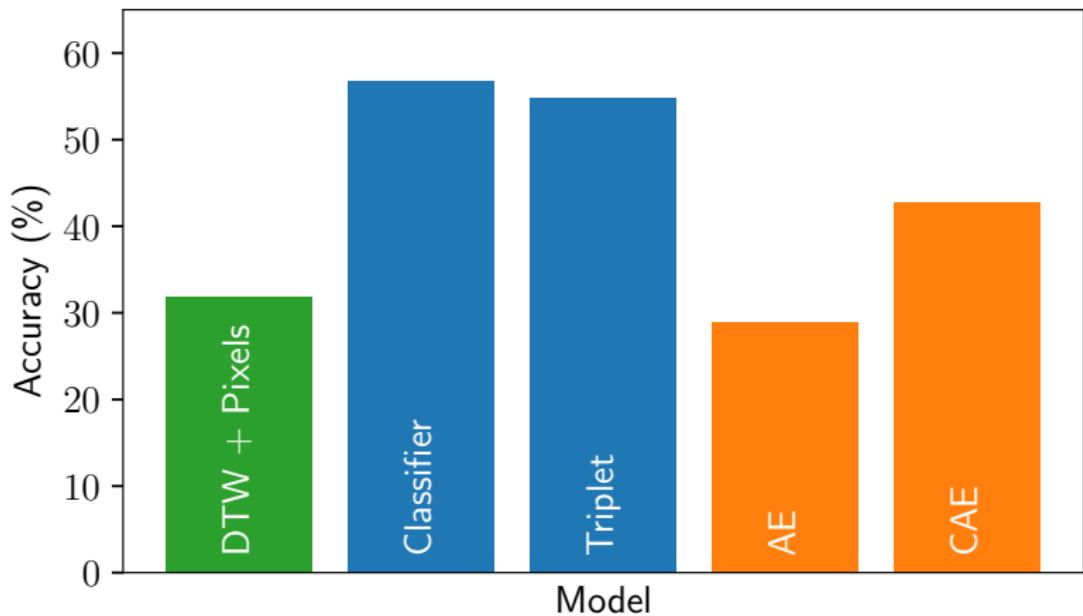
2. Unsupervised models



Kamper, "Truly unsupervised acoustic word embeddings using weak top-down constraints in encoder-decoder models," ICASSP, 2019.

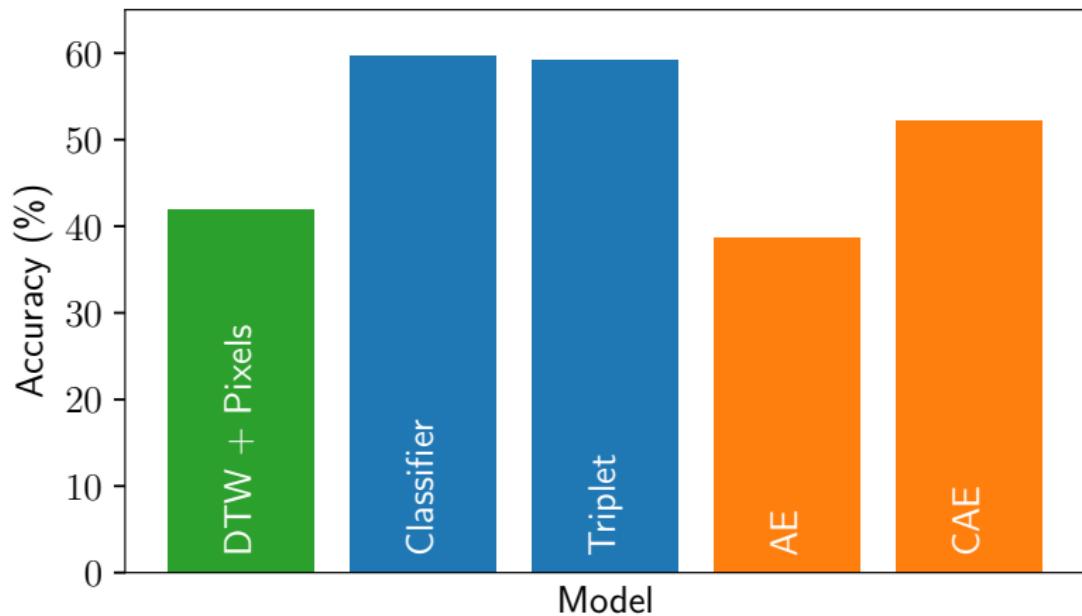
Evaluation: Multimodal one-shot matching

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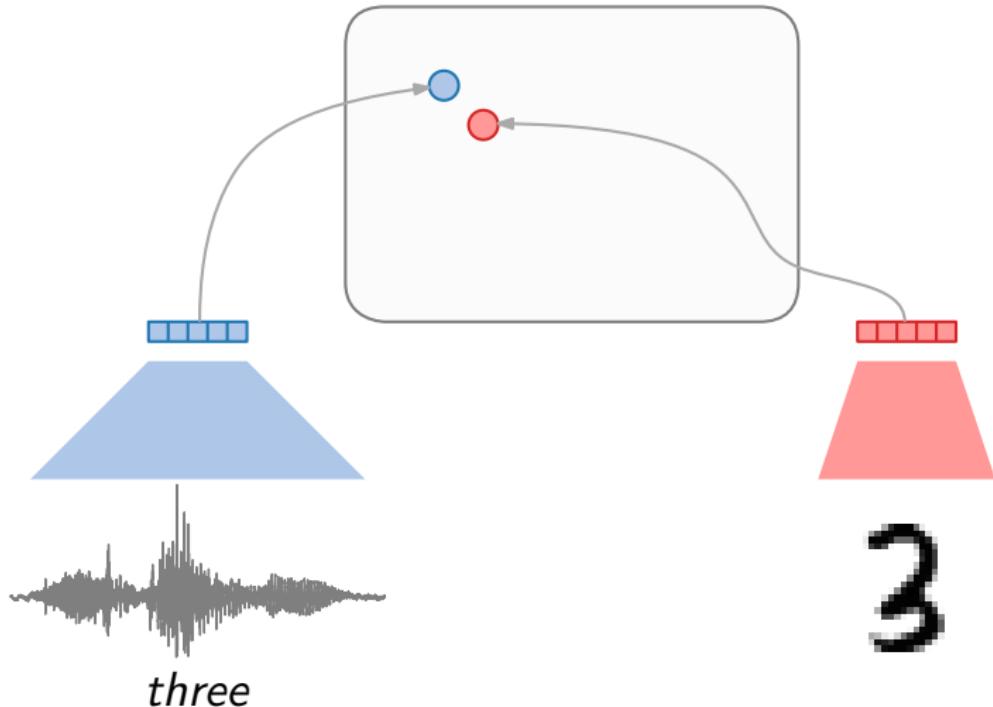
Nortje and Kamper, "Unsupervised vs. transfer learning for multimodal one-shot matching of speech and images," *Interspeech*, 2020.

Evaluation: Multimodal five-shot matching

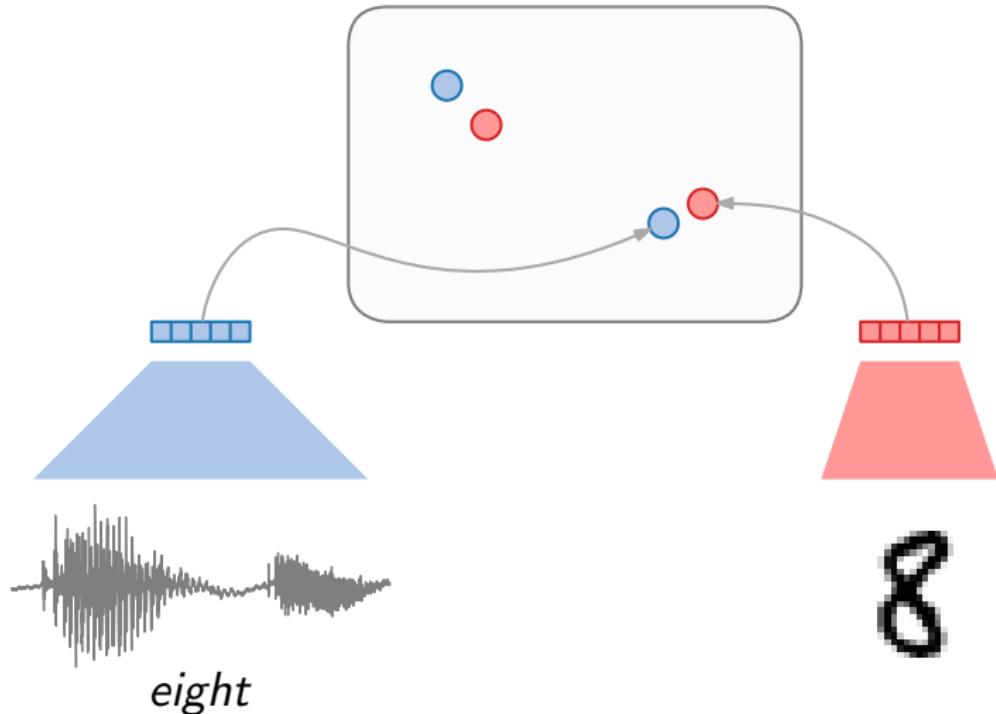


Nortje and Kamper, "Unsupervised vs. transfer learning for multimodal one-shot matching of speech and images," *Interspeech*, 2020.

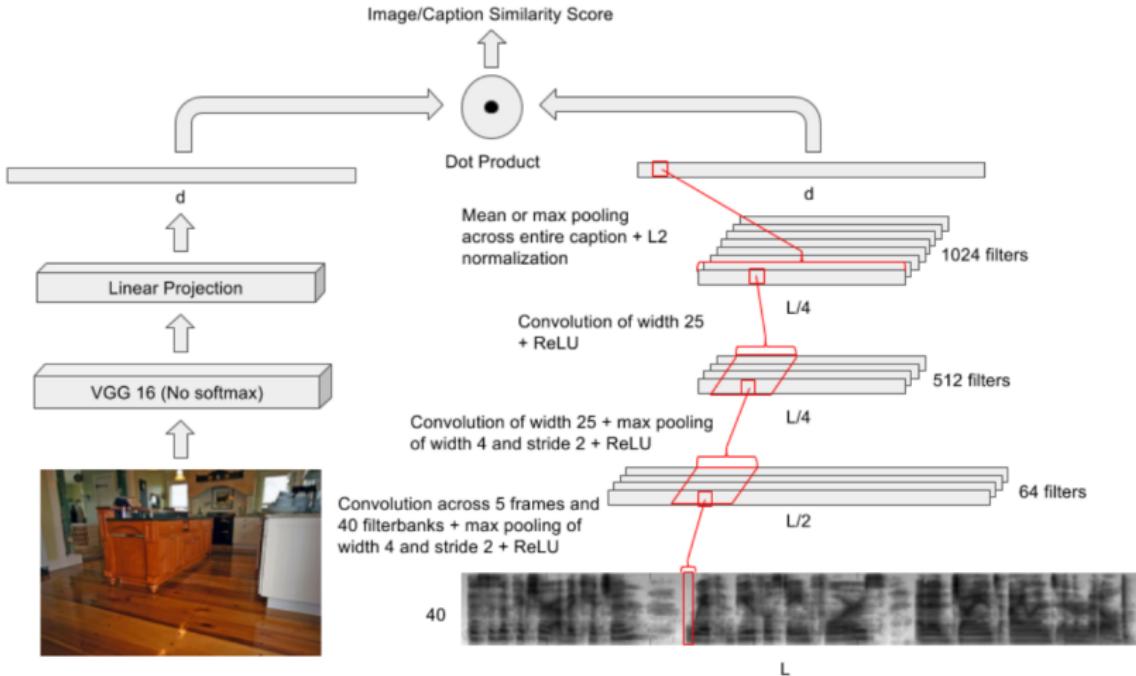
3. A direct approach?



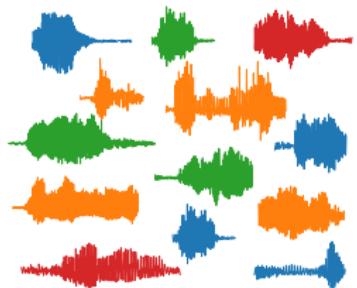
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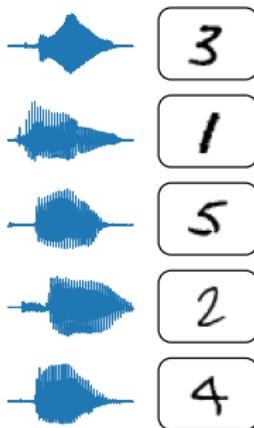
3. A direct approach?



3. Pair mining for a direct model



Unlabelled speech



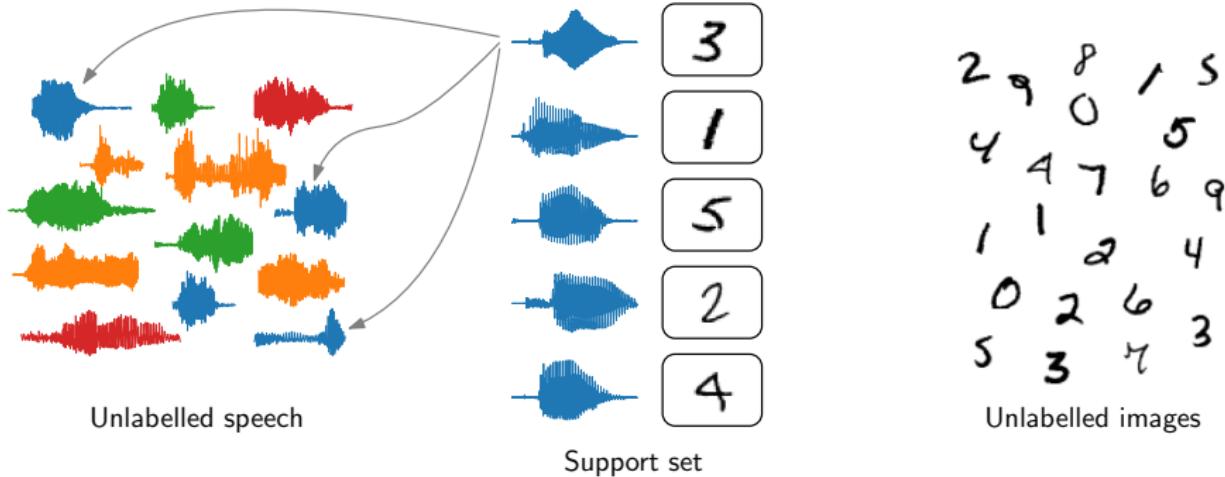
Support set

A grid of handwritten digits arranged in four columns and six rows. The digits are handwritten in black ink on a white background.

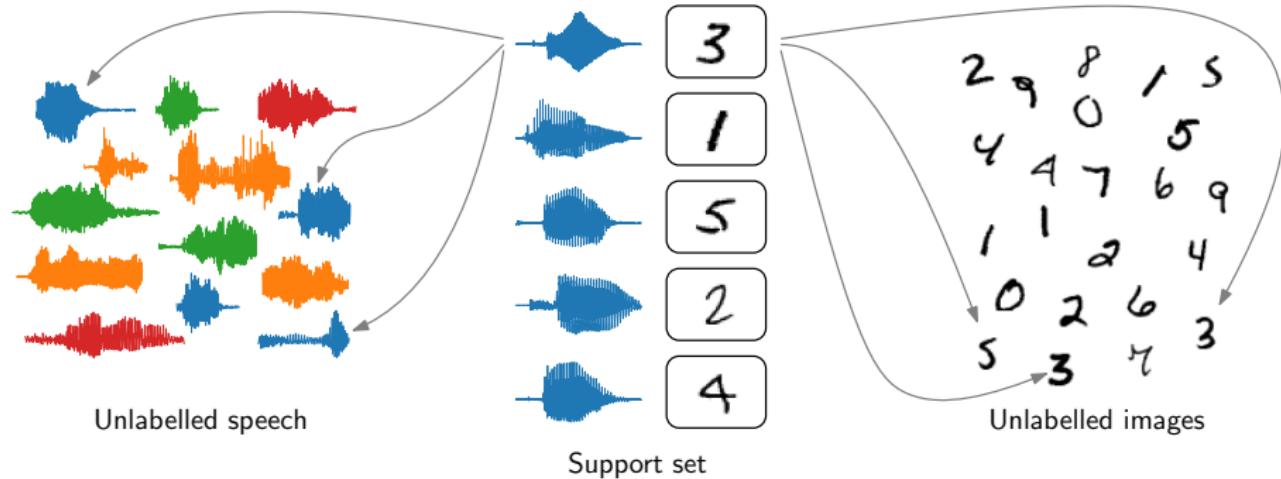
2	9	8	1
4	4	0	5
1	4	7	6
0	1	2	9
5	2	6	4
3	3	7	3

Unlabelled images

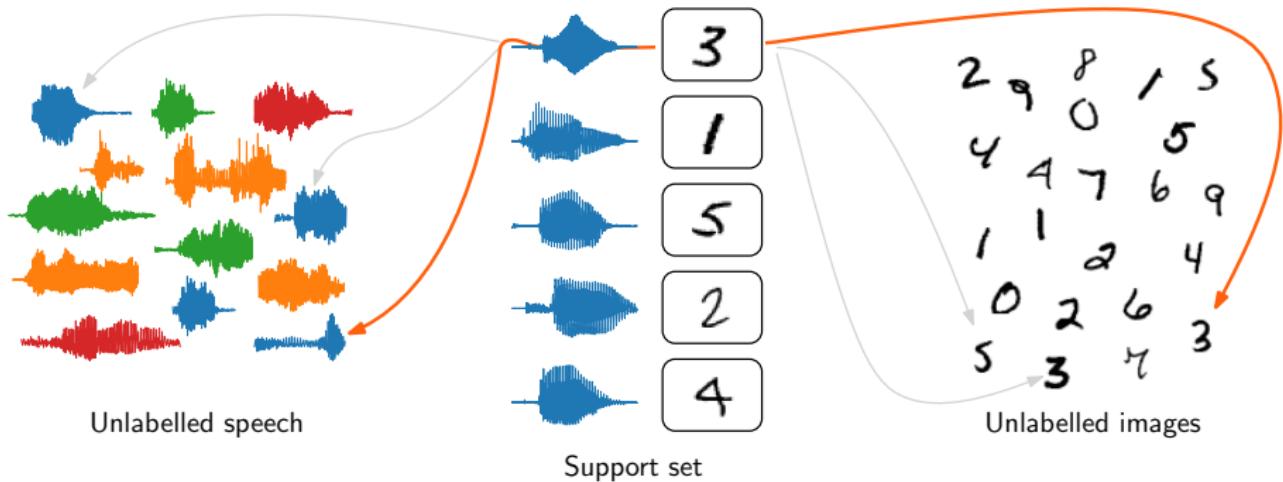
3. Pair mining for a direct model



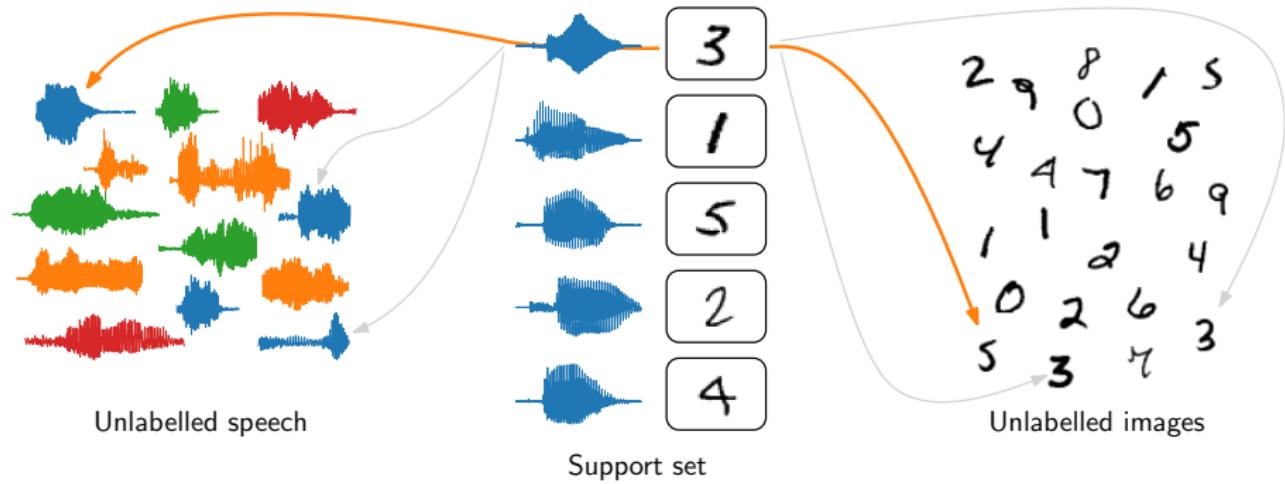
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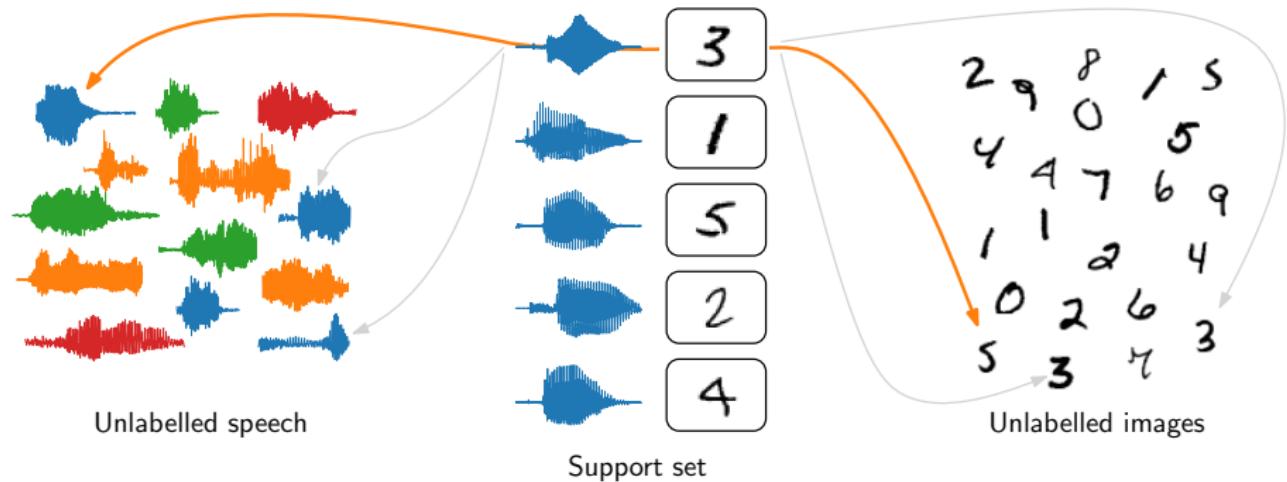
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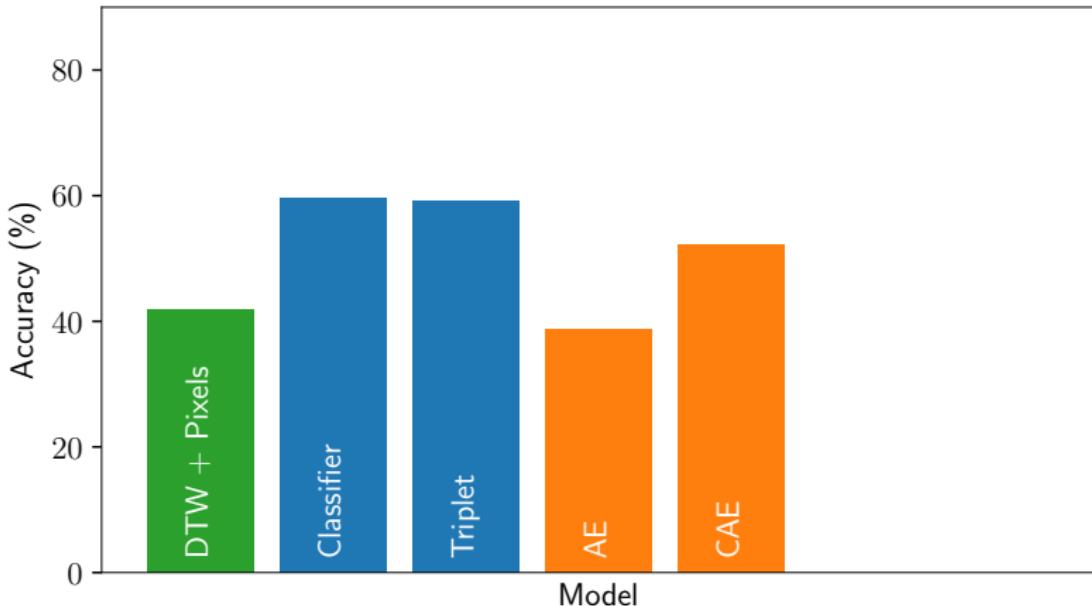


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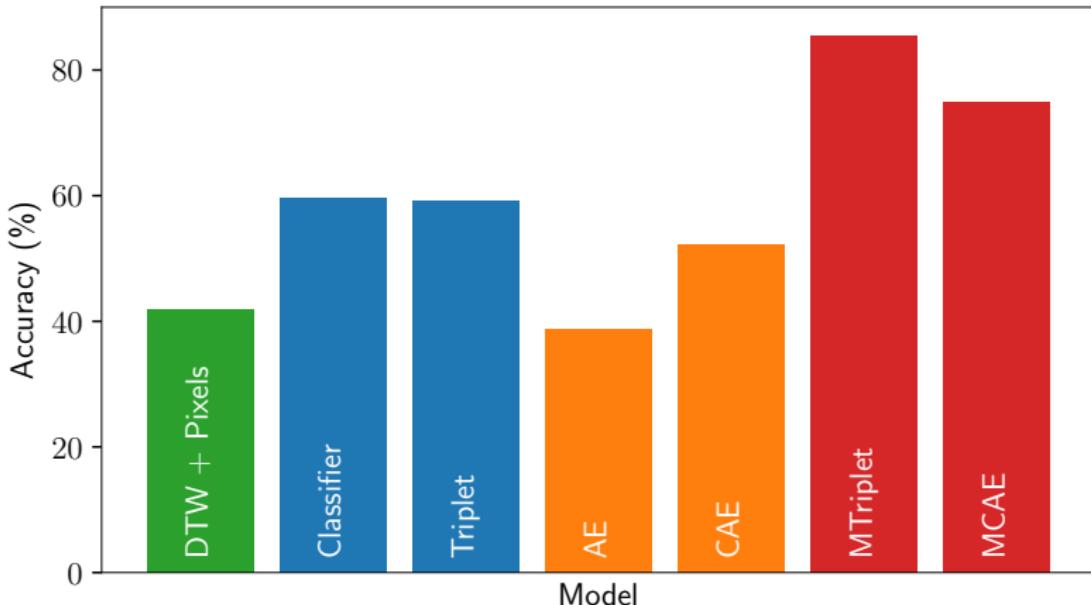


Involves combining (1) transfer learning and (2) unsupervised learning

Evaluation: Multimodal five-shot matching



Evaluation: Multimodal five-shot matching



Summary and conclusion

Summary and looking forward

1. What can we learn from unlabelled speech audio, i.e. radio?
— Part 1
2. What can we learn from co-occurring (grounding) signals like vision, i.e. television?
— Part 2
3. What can we learn from interaction/feedback from our environment and other “agents”?

Summary and looking forward

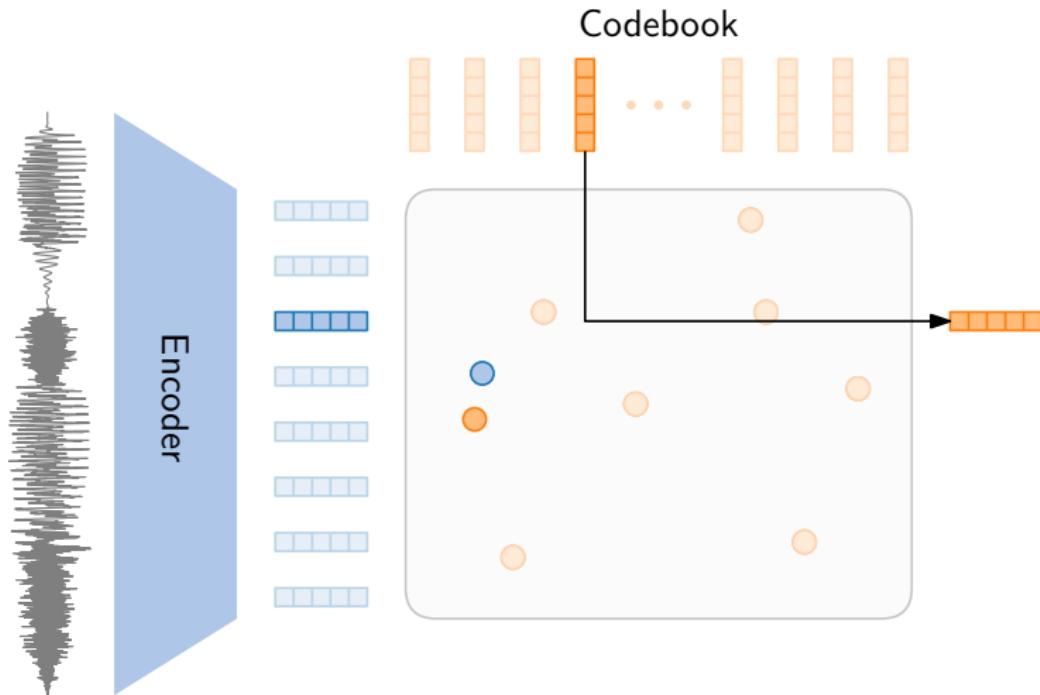
0. What structures/knowledge should we start with/build in?
1. What can we learn from unlabelled speech audio, i.e. radio?
— Part 1
2. What can we learn from co-occurring (grounding) signals like vision, i.e. television?
— Part 2
3. What can we learn from interaction/feedback from our environment and other “agents”?

<https://github.com/bshall/ZeroSpeech/>

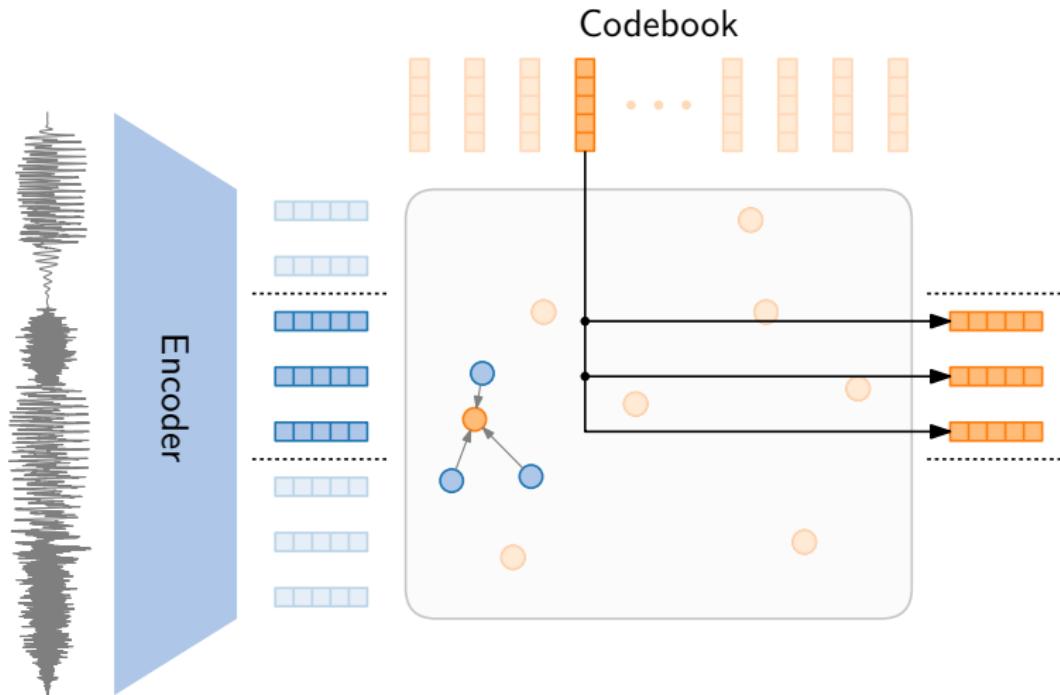
<https://github.com/bshall/VectorQuantizedCPC/>

https://github.com/LeanneNortje/multimodal_speech-image_matching/

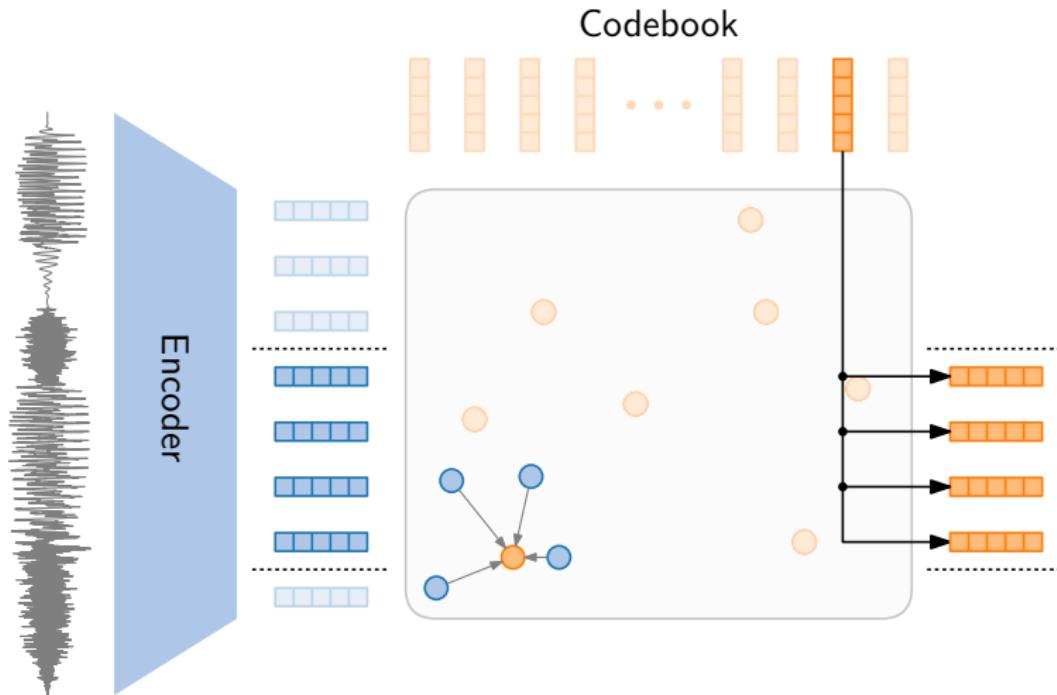
Segmentation on top of vector quantisation



Segmentation on top of vector quantisation



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