Multi-Task and Transfer Learning in Low-Resource Speech Recognition

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Thanks!

Keeping me on track: Tom, Mihai, Mike, Clay

Keeping me funded: Dorian, Georgia, Shelley

Keeping me happy: Bill, Nick, Nick, MC, Shiloh, Megan, Adam, Ryan, Samwise, Gus

Roadmap

- Overview of ASR
- Overview of Transfer Learning
  - Multi-Task Learning
  - Copy-Paste Transfer
- Multi-Task Learning Studies
  - Linguistic Tasks
  - Engineered Tasks
- Copy-Paste Transfer Studies
  - Multilingual Transfer
  - Model Interpretability
- Conclusion

Introduction

Motivation

Current training methods
for automatic speech recognition
require massive collections of data.

However, most use-cases have
little — if any — available data.

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But we can exploit similar use-cases!

Transfering Bias

Useful bias comes from a source **domain**

Transfering Bias

Useful bias comes from a source **domain**

source **Dataset**

Transfering Bias

Useful bias comes from a source **domain**

source **Dataset**

-or-

source **Model**

Example of Domain

Bias Source

Resource

source Dataset →

-or-

source Model →

Example of Domain

Bias Source	**Resource**
source Dataset →	English Speech Corpus
-or-	-or-
source Model →	Trained English Model

Transfering Bias

Bias Source **Transfer Method**

source Dataset →

-or-

source Model →

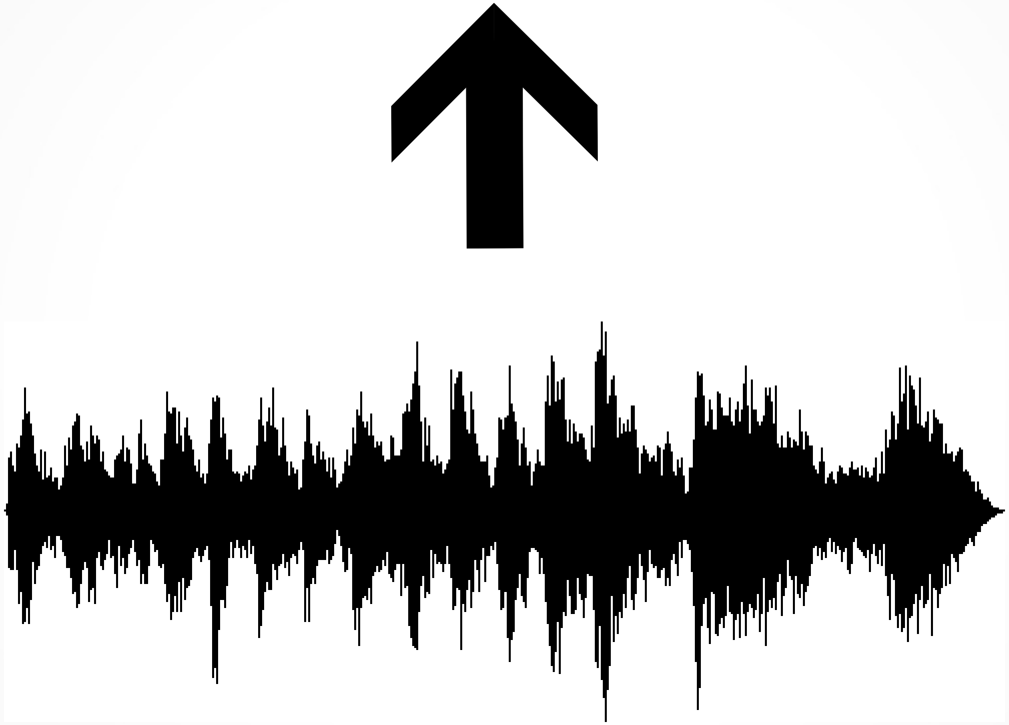
Transfering Bias

Bias Source	**Transfer Method**
source Dataset →	Multi-Task Learning
-or-	-or-
source Model →	Copy-Paste Transfer

Automatic Speech Recognition?

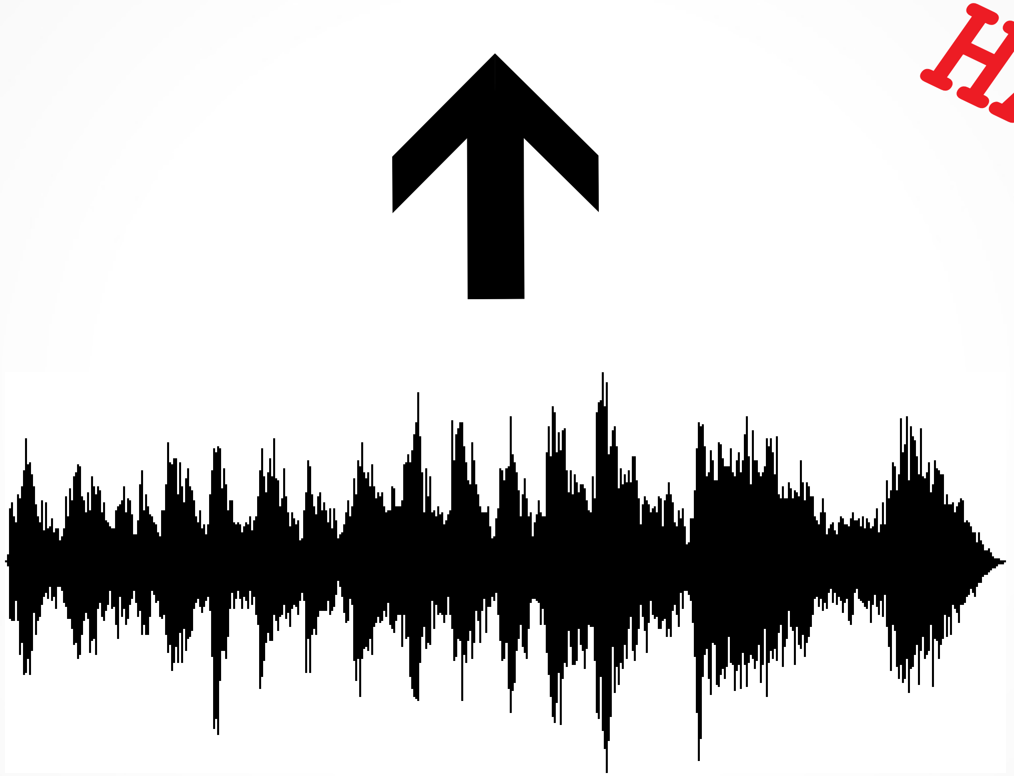
Automatic Speech Recognition

"THE DOG"



Automatic Speech Recognition

"THE DOG"



HARD

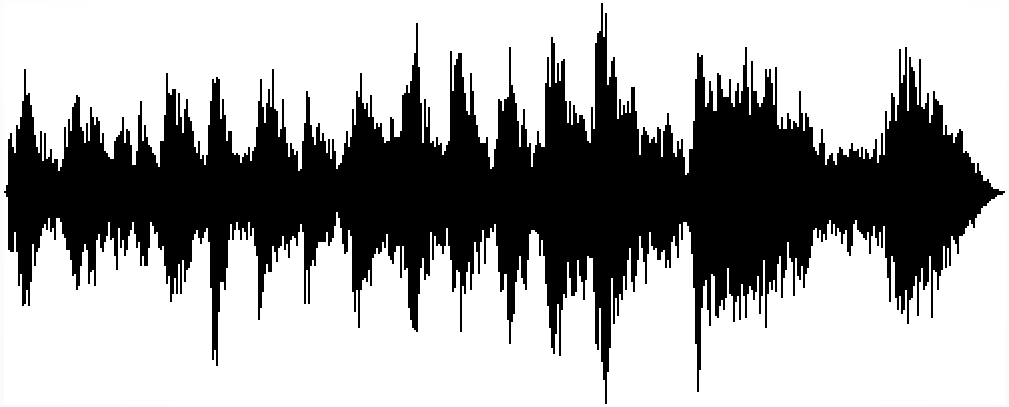
Automatic Speech Recognition

"THE DOG"

↑

T H E D O G

↑



EASIER

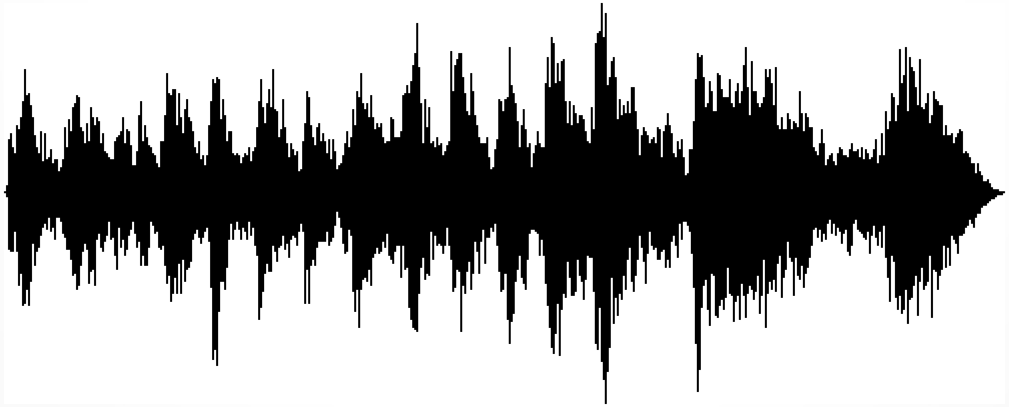
Automatic Speech Recognition

"THE DOG"

↑

T H E D O G ← *"Phoneme-like" units*

↑



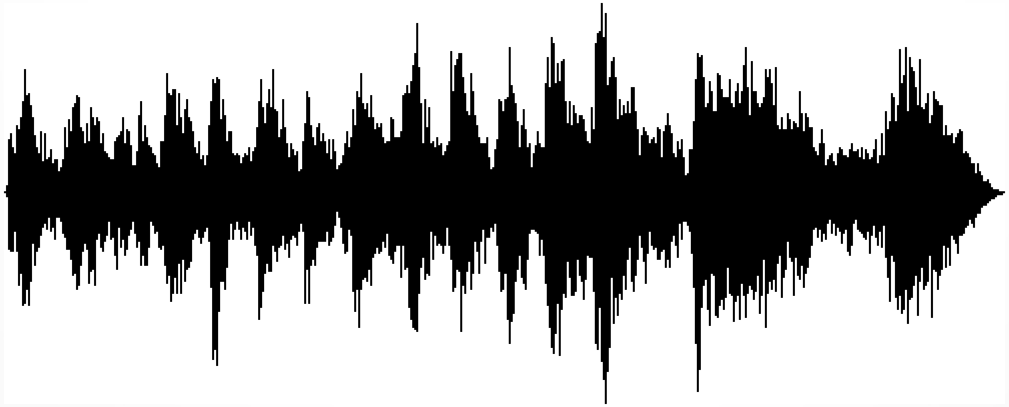
Automatic Speech Recognition

"THE DOG"

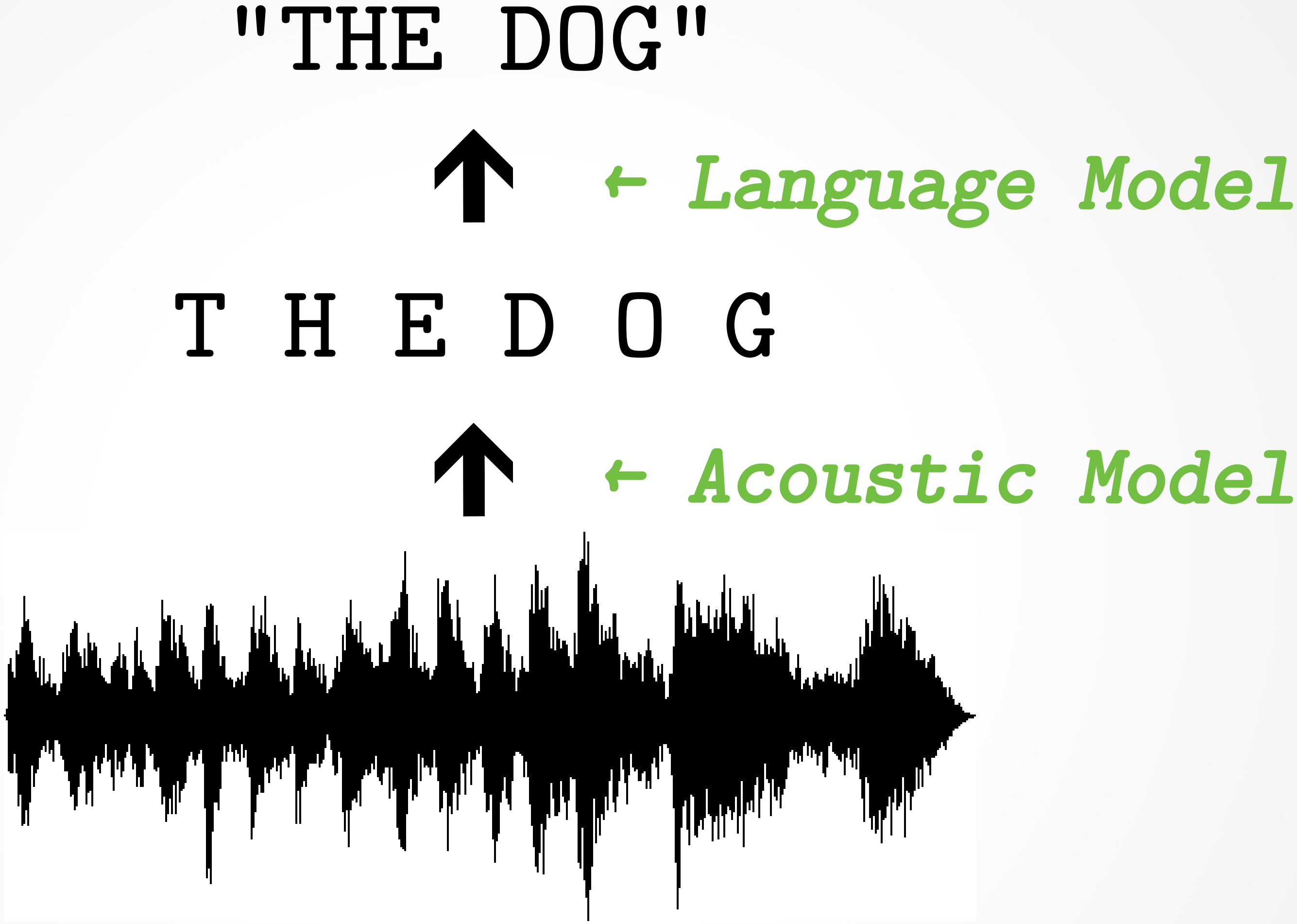
↑

T H E D O G

↑ ← *Acoustic Model*



Automatic Speech Recognition



"THE DOG"

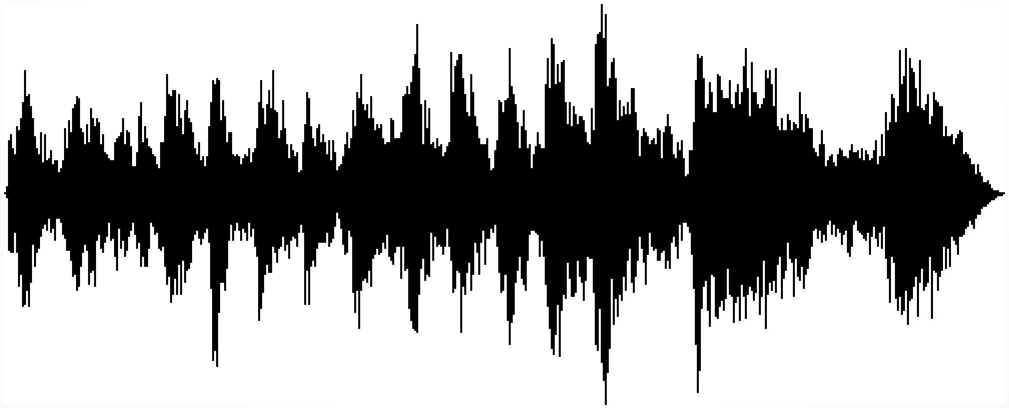
← *Language Model*

T H E D O G

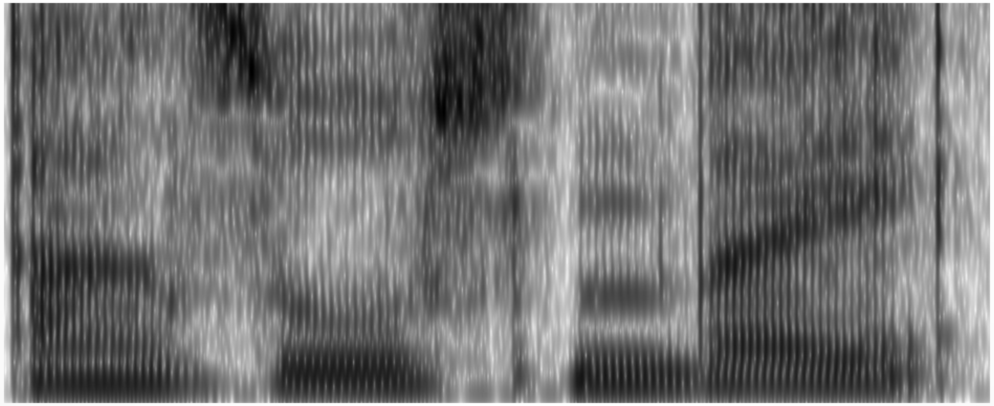
← *Acoustic Model*

ASR Acoustic Modeling

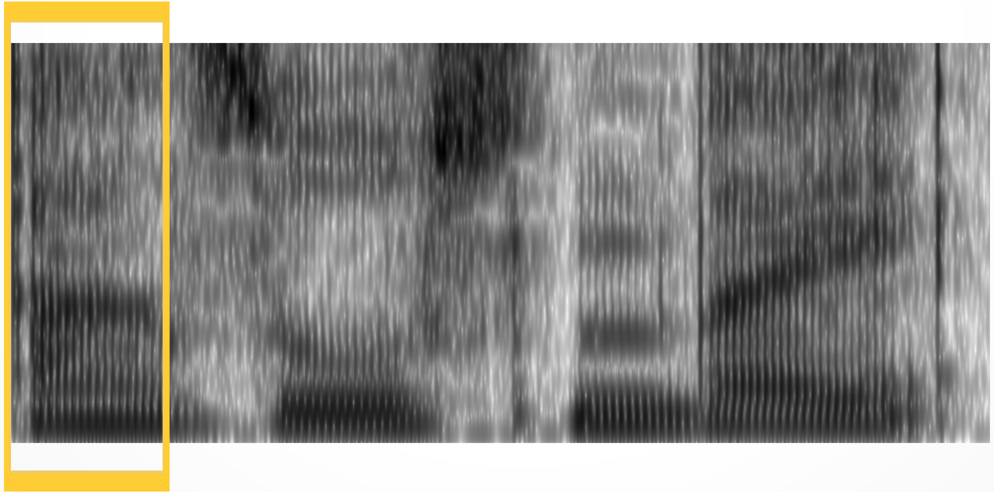
Acoustic Model



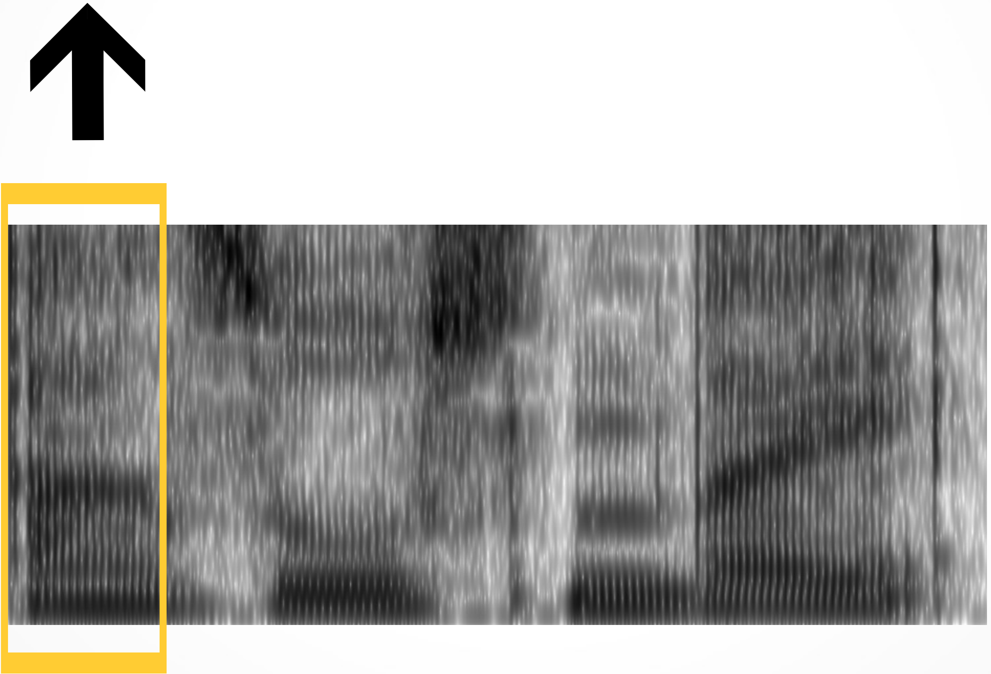
Acoustic Model



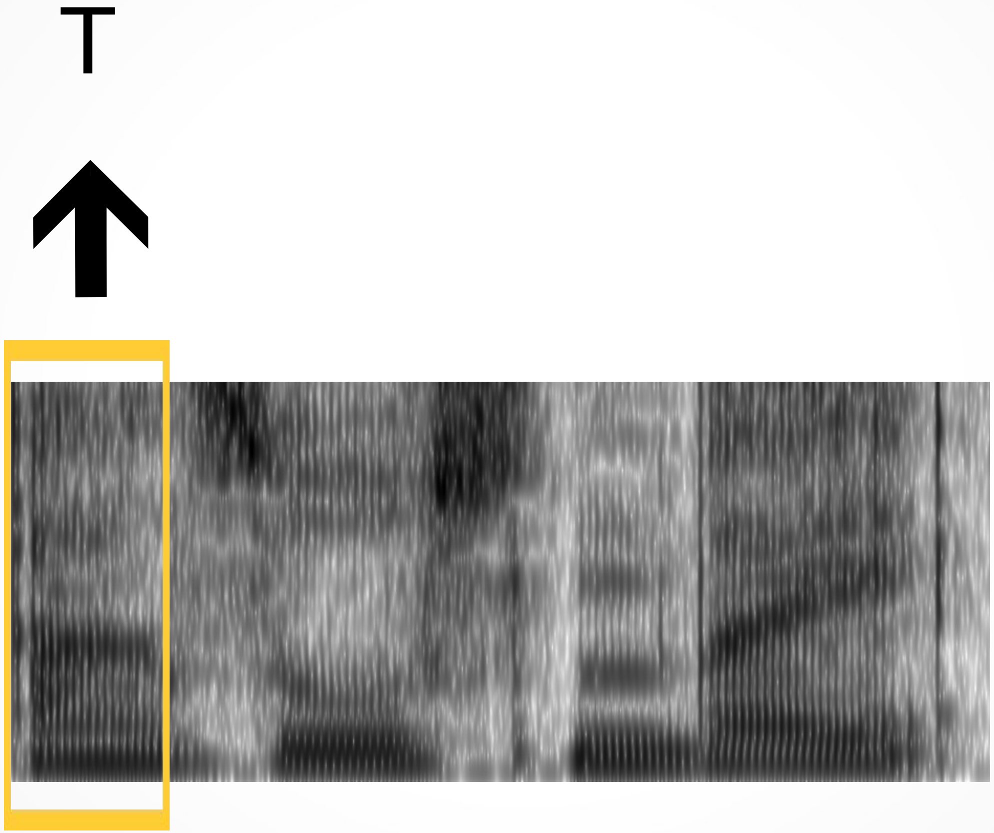
Acoustic Model



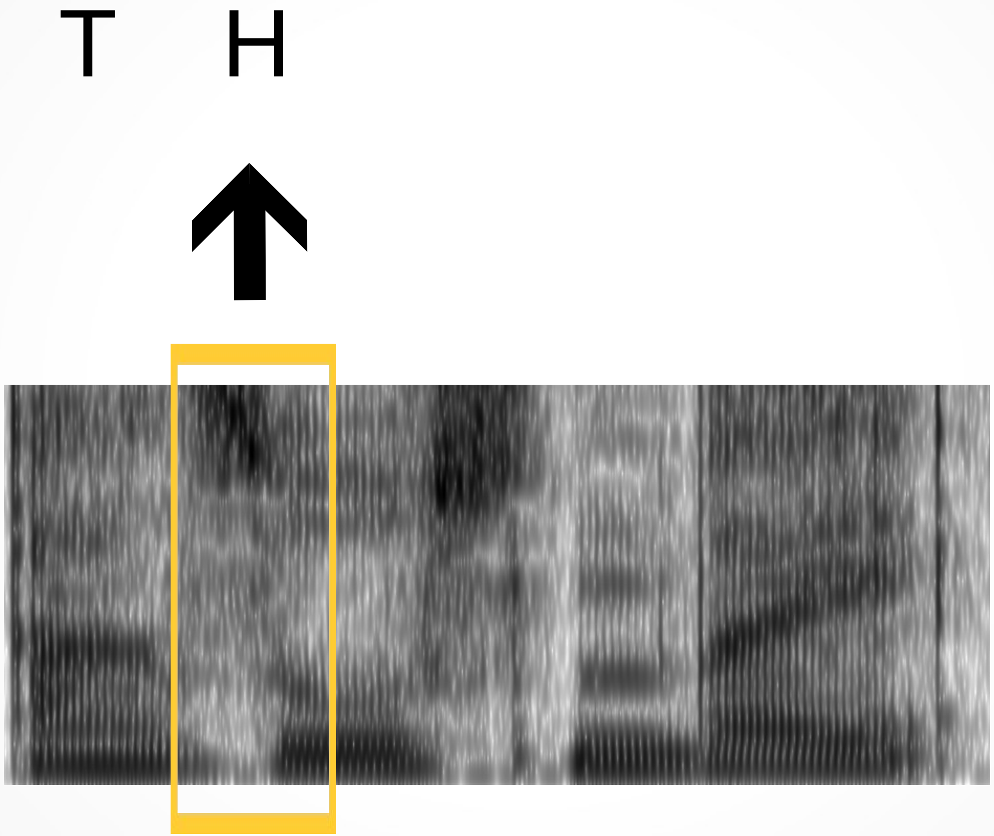
Acoustic Model



Acoustic Model



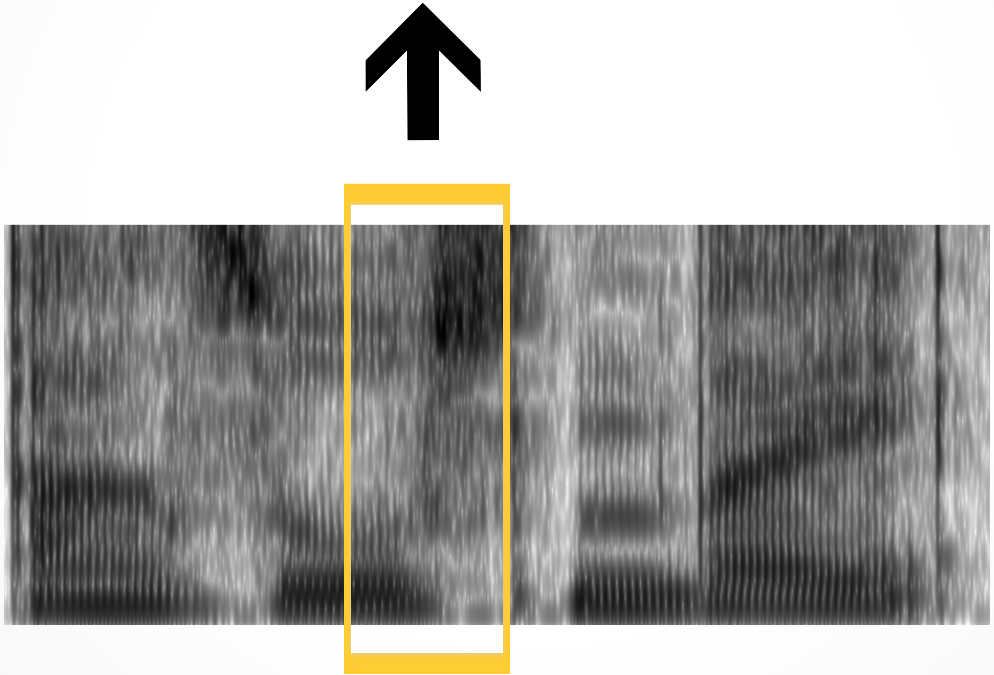
Acoustic Model



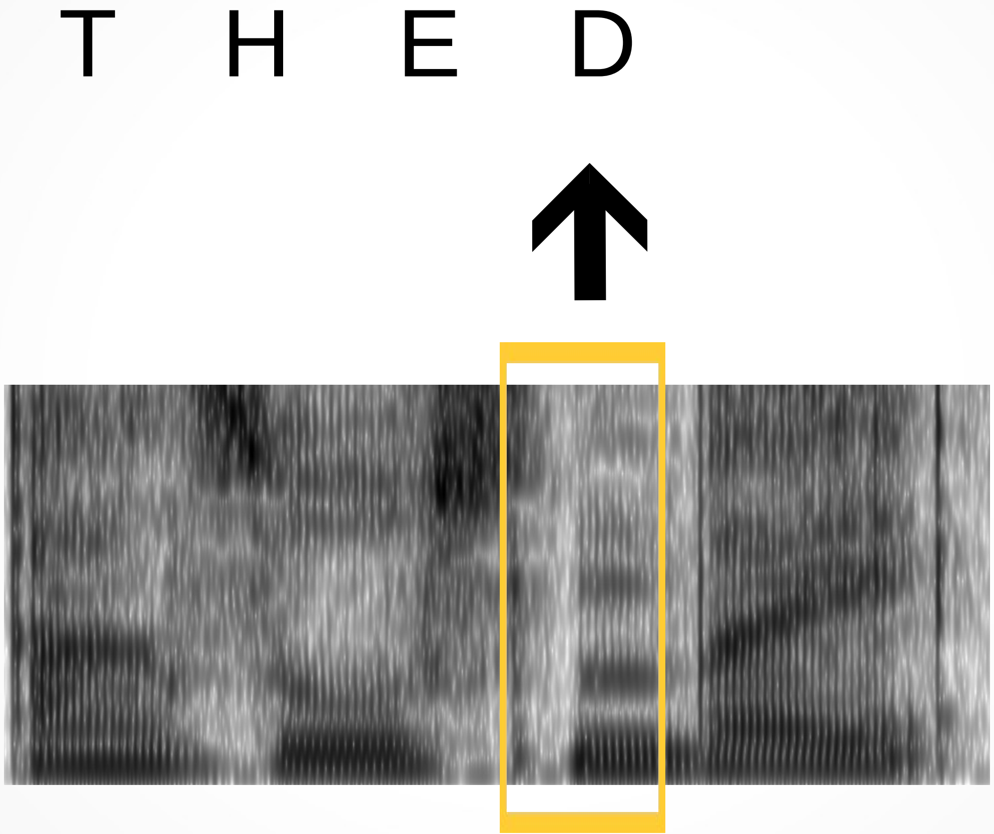
T H

Acoustic Model

T H E

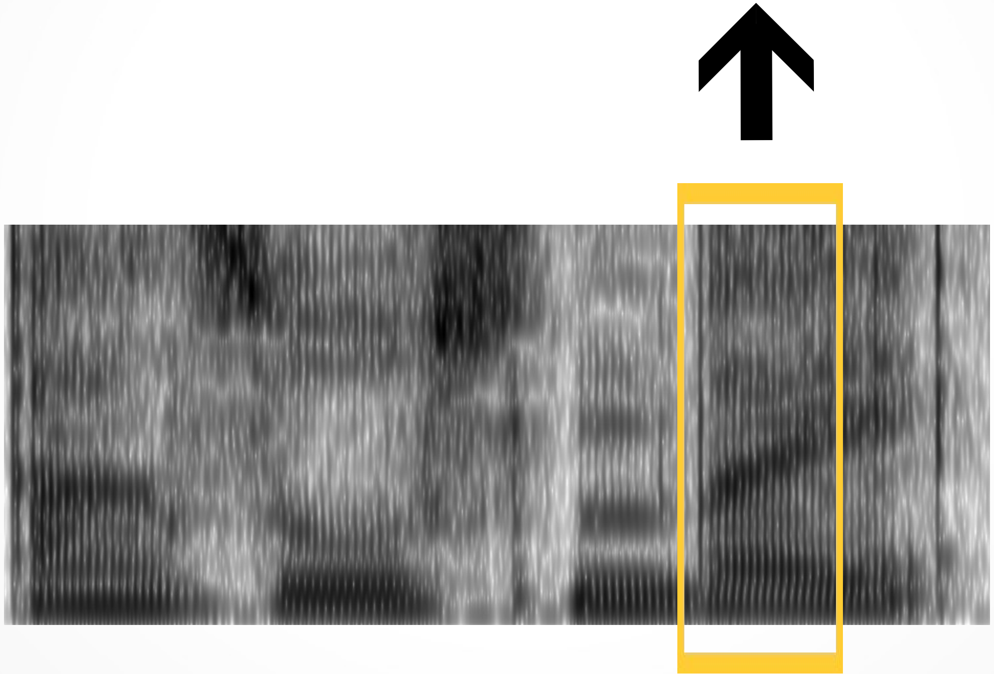


Acoustic Model



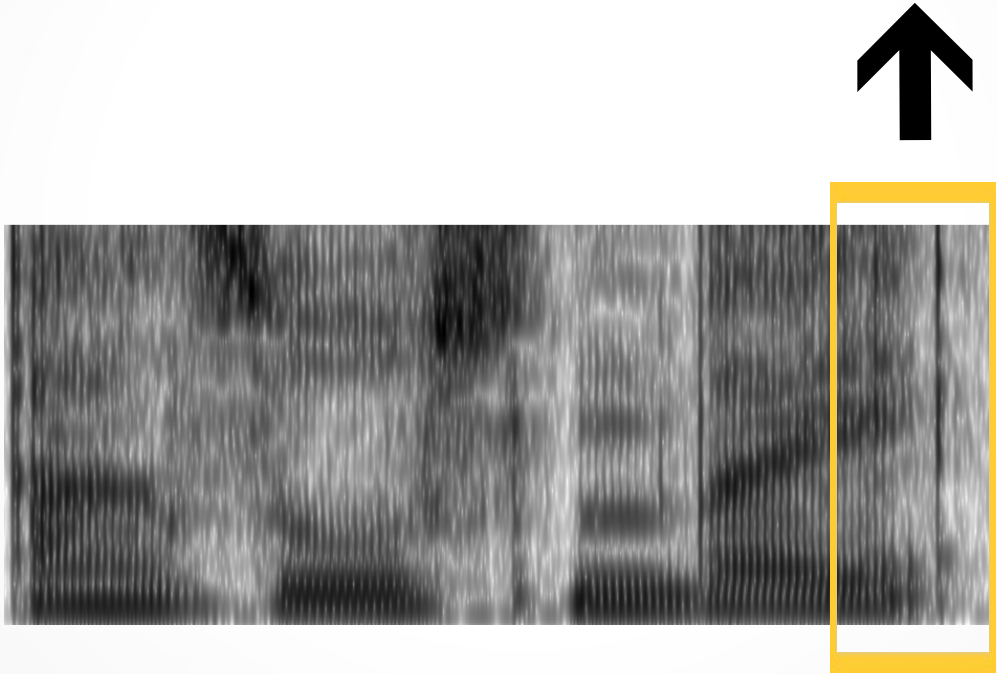
Acoustic Model

T H E D O

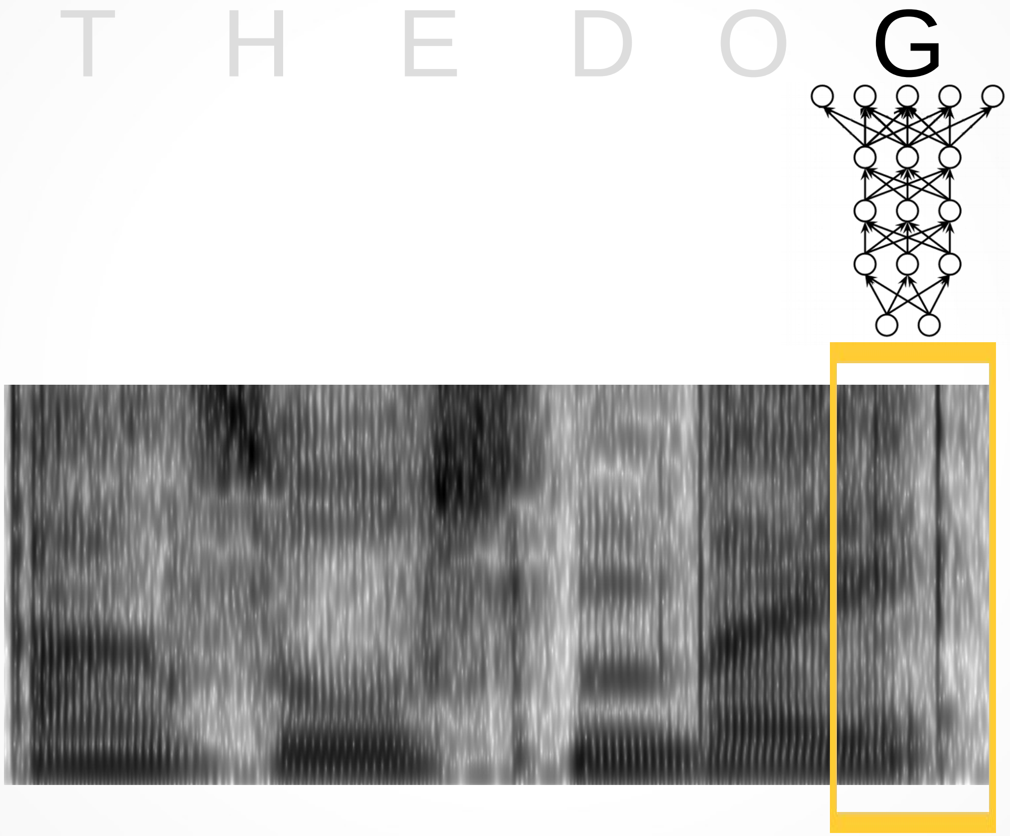


Acoustic Model

T H E D O G

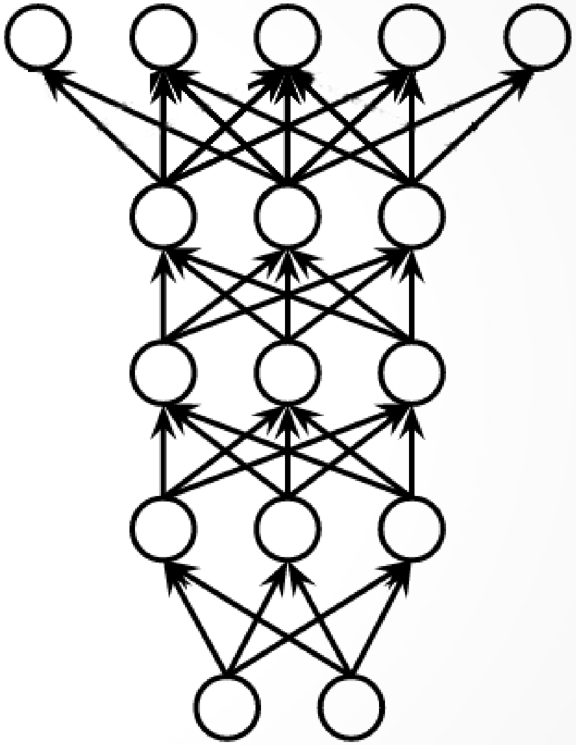


Acoustic Model



T H E D O G

Acoustic Model

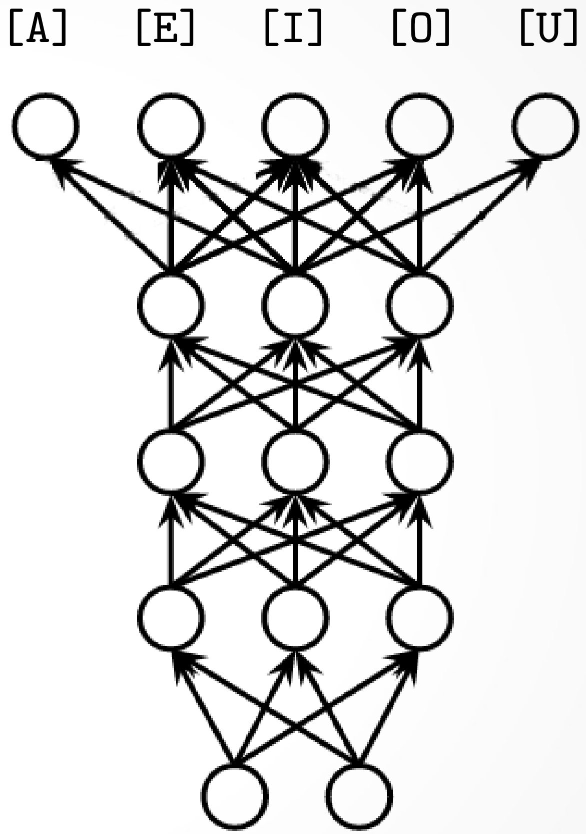


Phonetic Labels

Audio Features

Acoustic Model

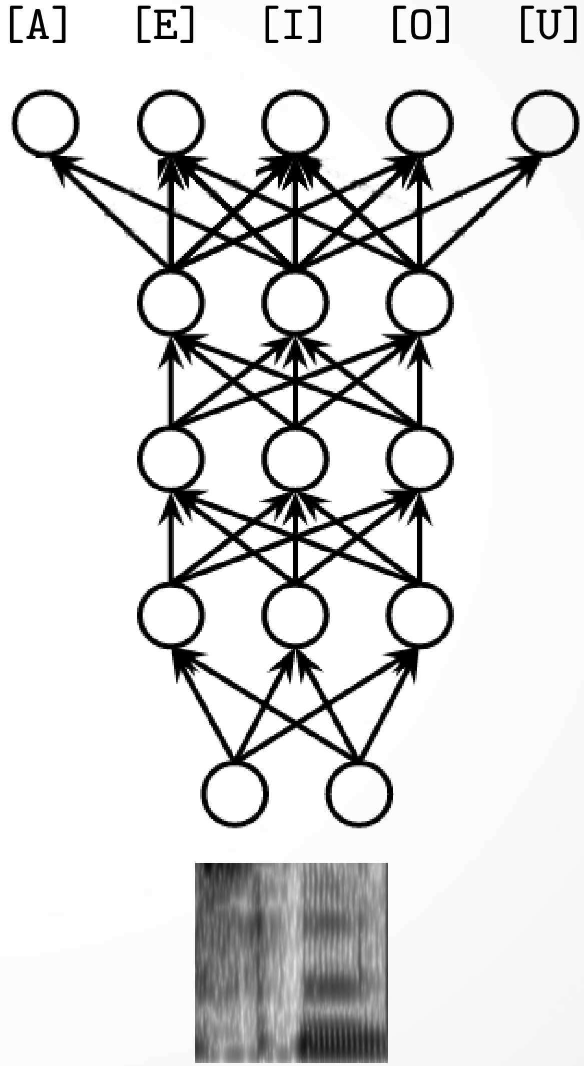
Phonetic Labels



Audio Features

Acoustic Model

Phonetic Labels

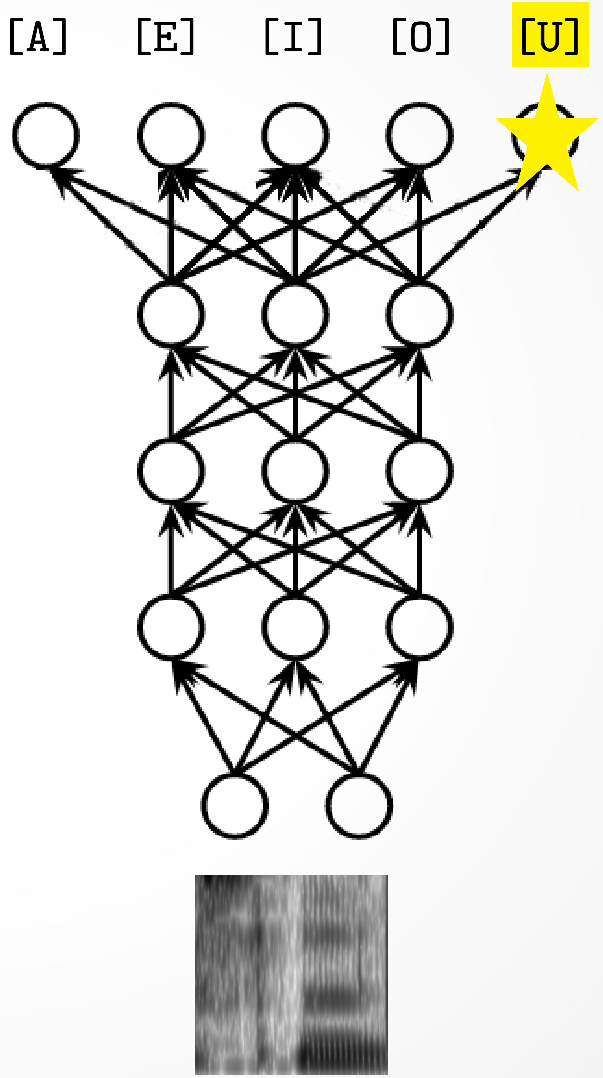


Audio Features

Acoustic Model

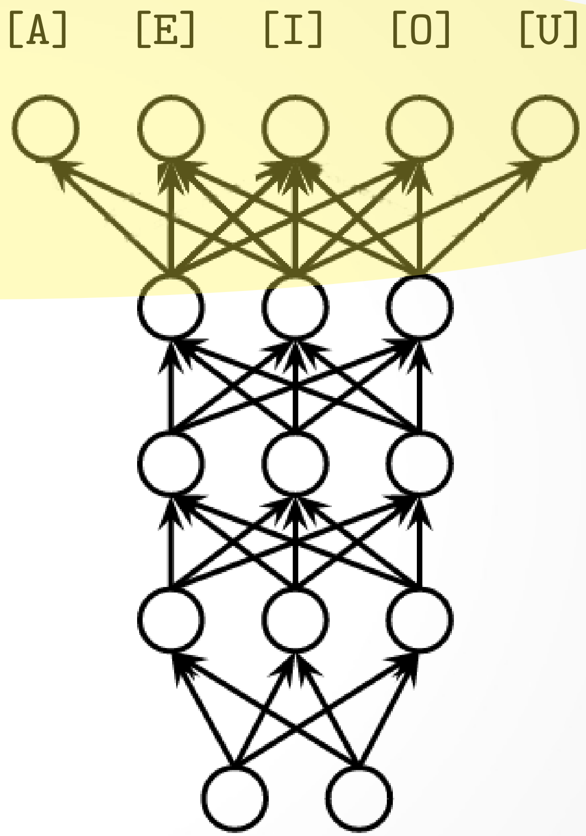
Phonetic Labels

Audio Features



Acoustic Model

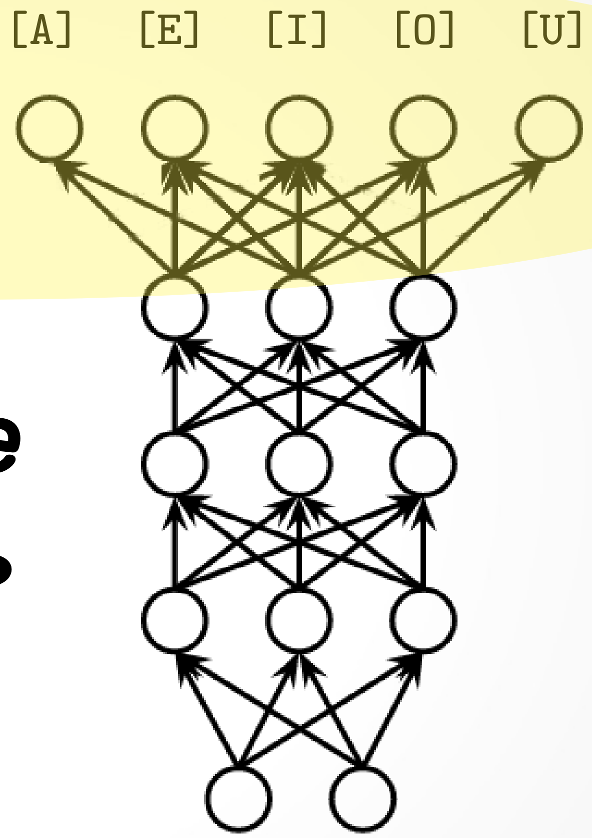
Phonetic Labels



Audio Features

Acoustic Model

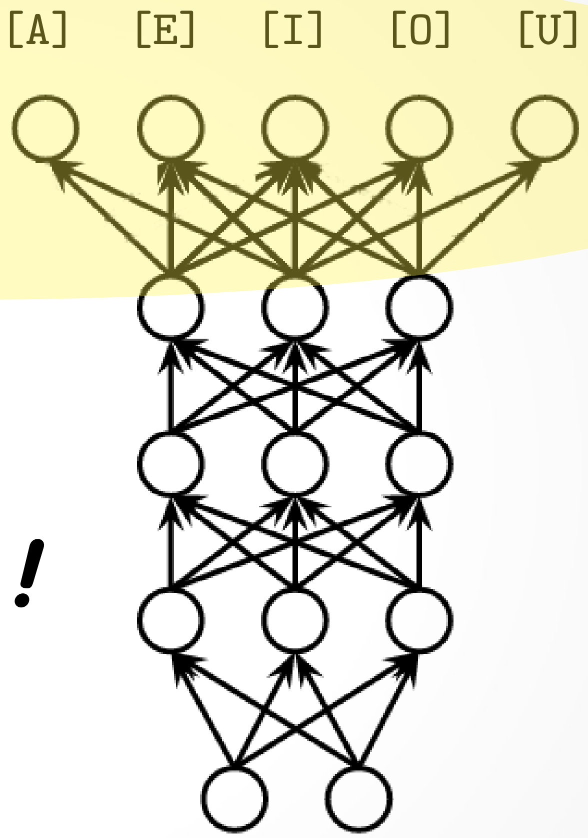
Phonetic Labels



Where do we get labels?

Audio Features

Acoustic Model

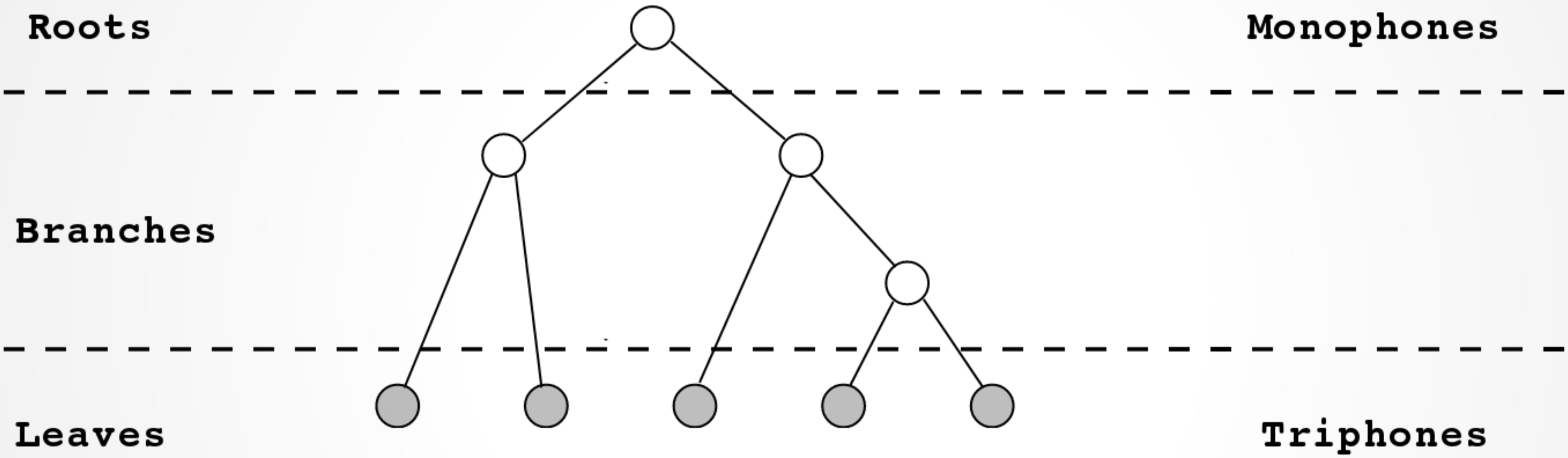


Phonetic Labels

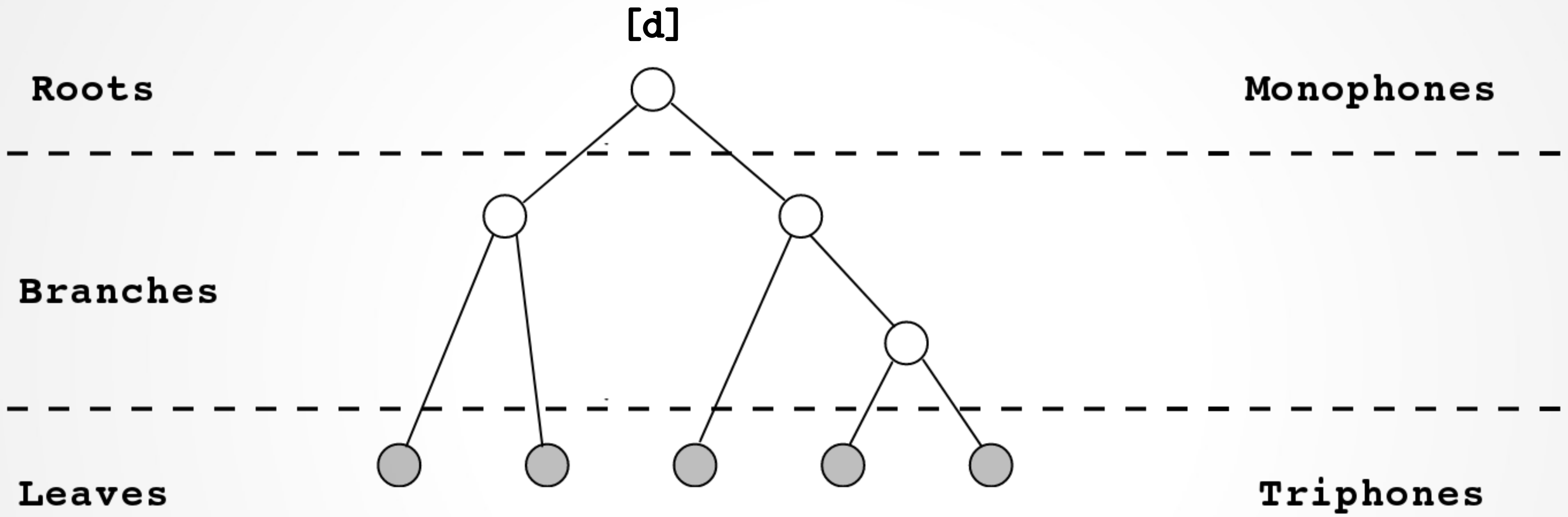
Happy little trees!

Audio Features

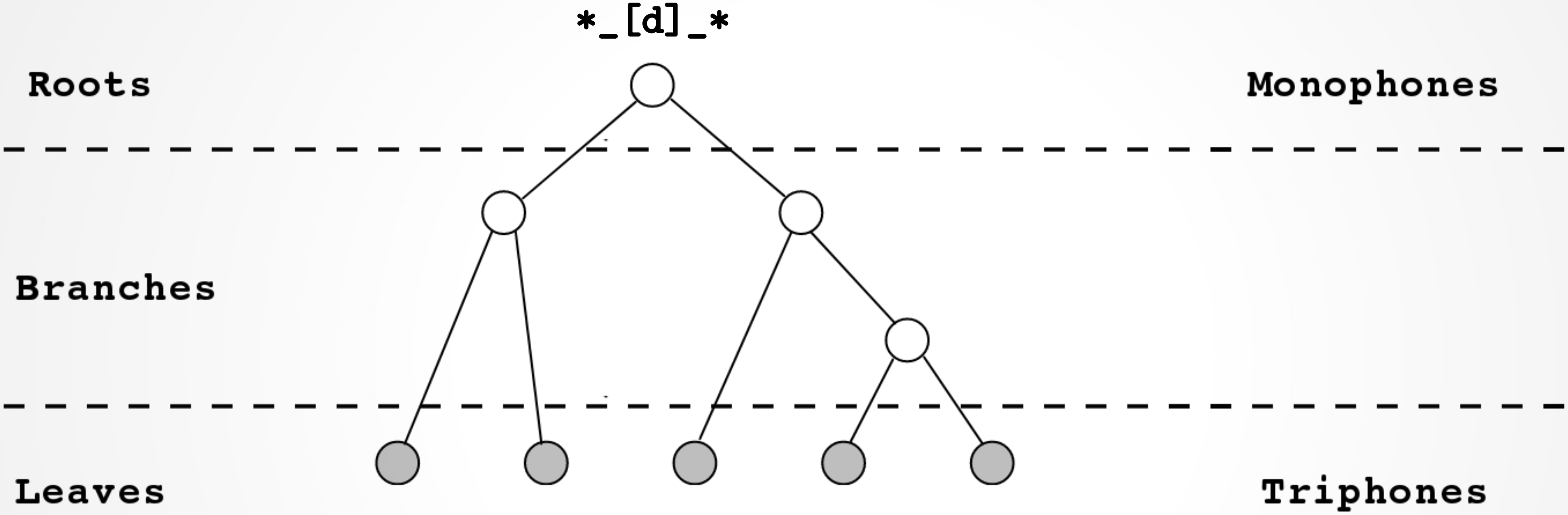
Phonetic Decision Tree



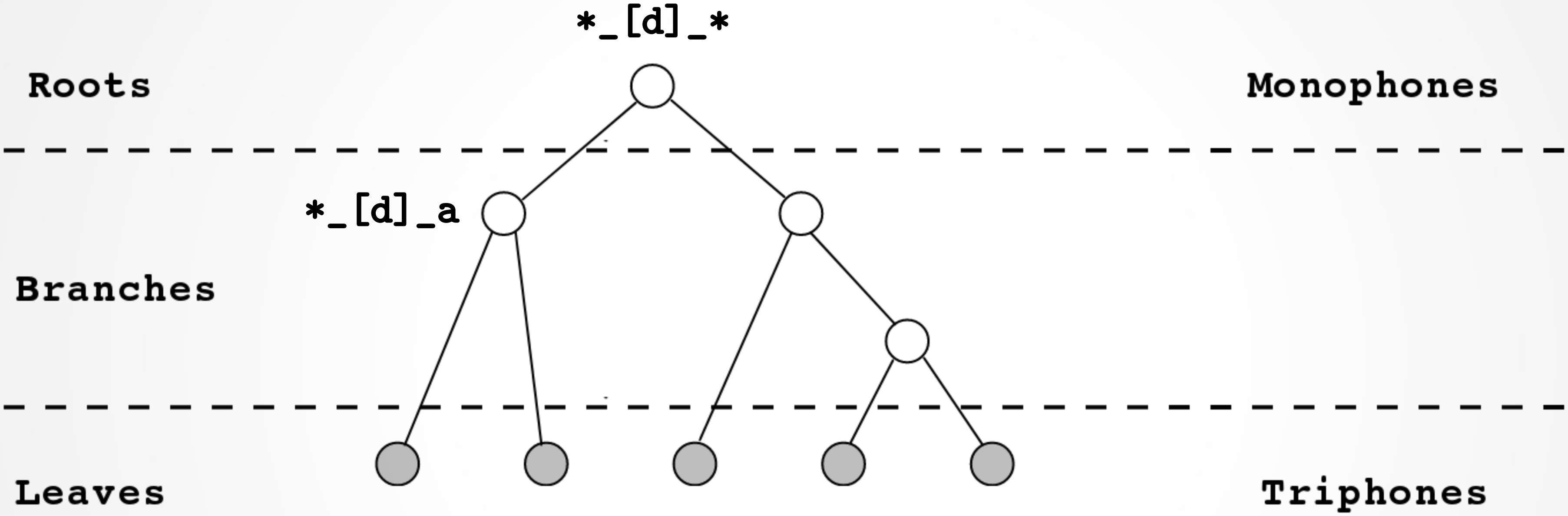
Phonetic Decision Tree



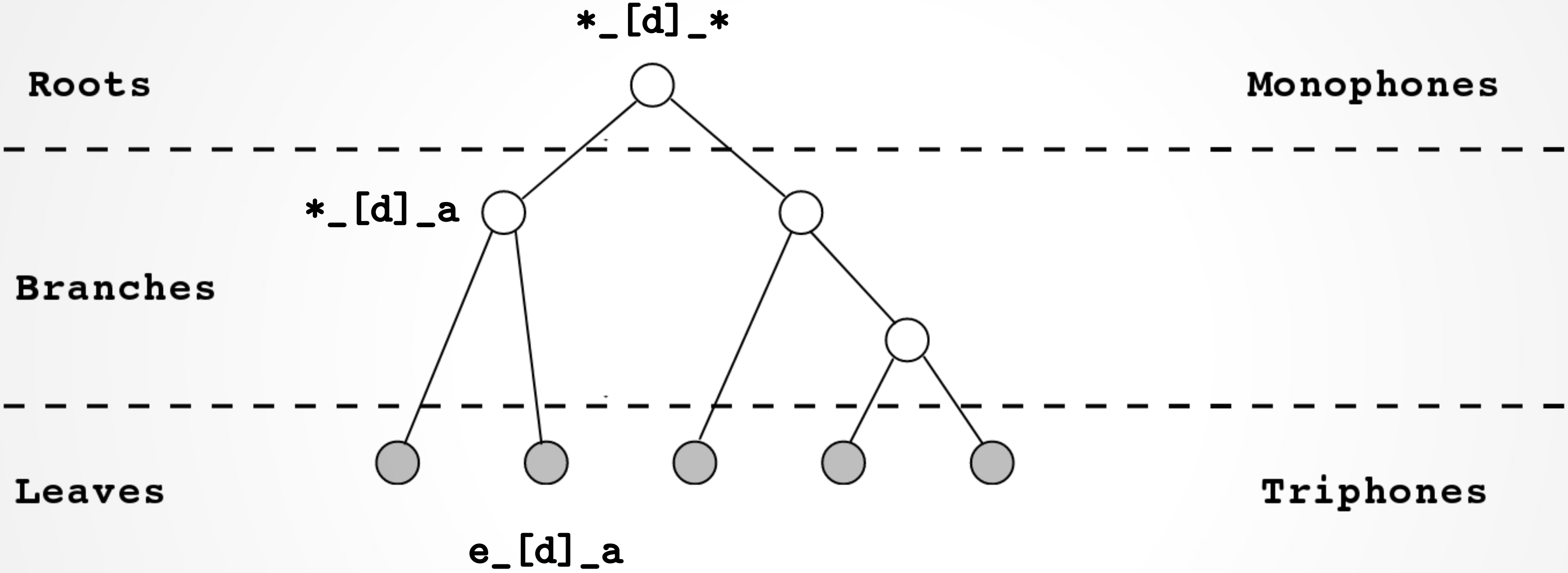
Phonetic Decision Tree



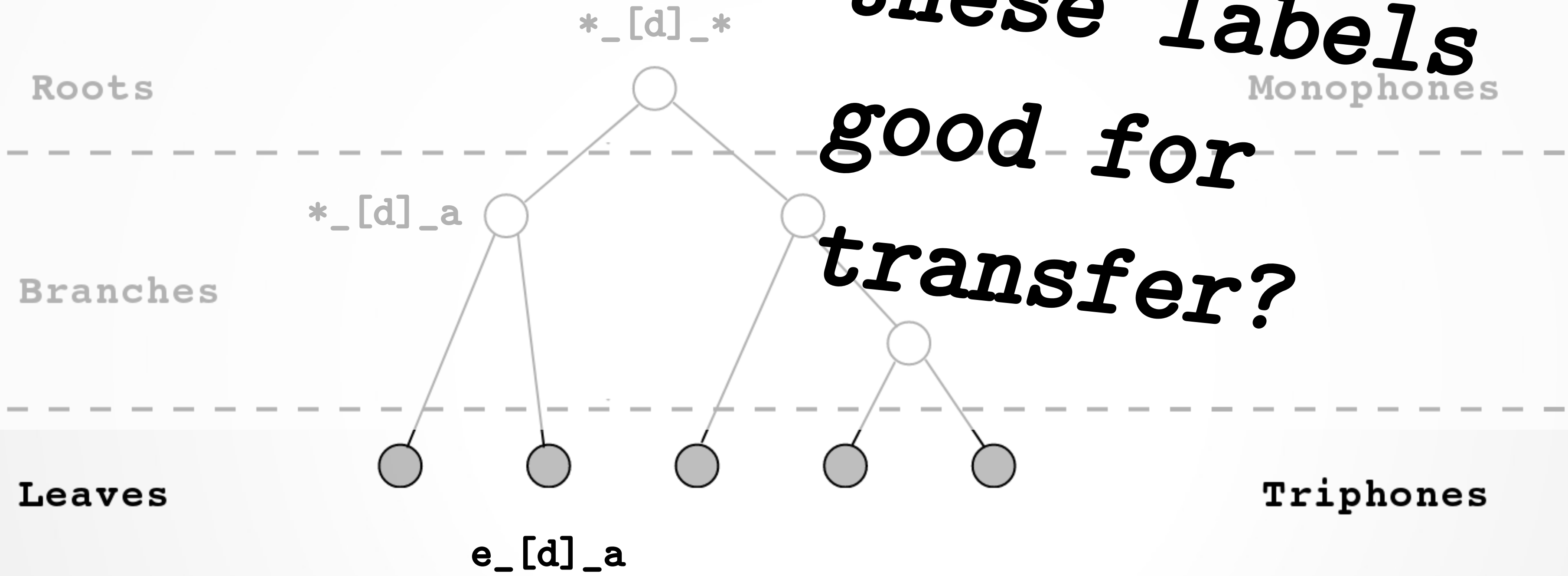
Phonetic Decision Tree



Phonetic Decision Tree



Phonetic Decision Tree



But… are these labels good for transfer?

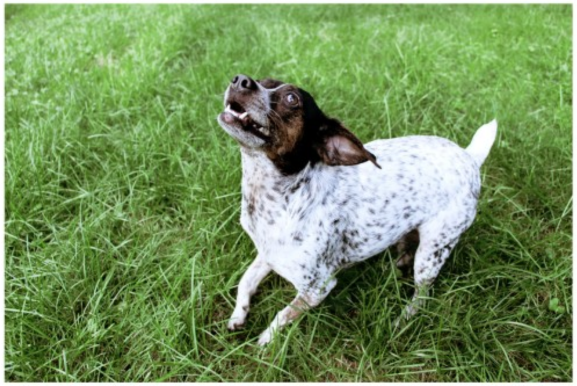
Multi-Task Learning

What is a task?

Single-Task Learning

{rottweiler}

{collie}

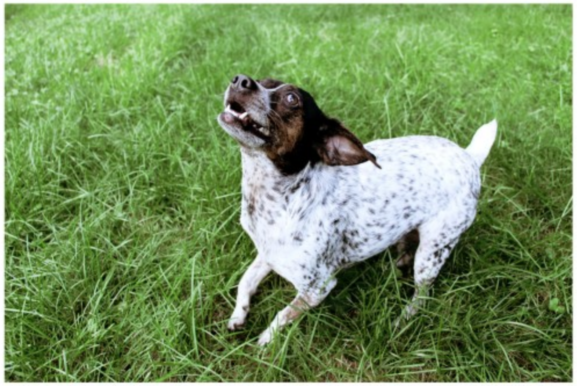


{terrier}

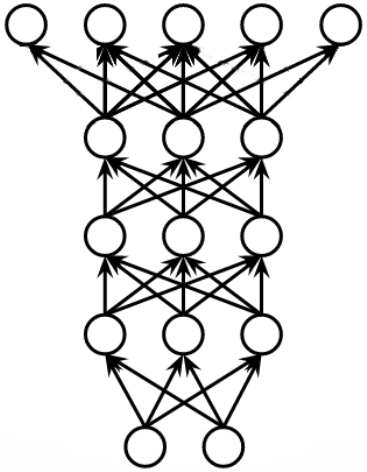
Single-Task Learning

{rottweiler}

{collie}



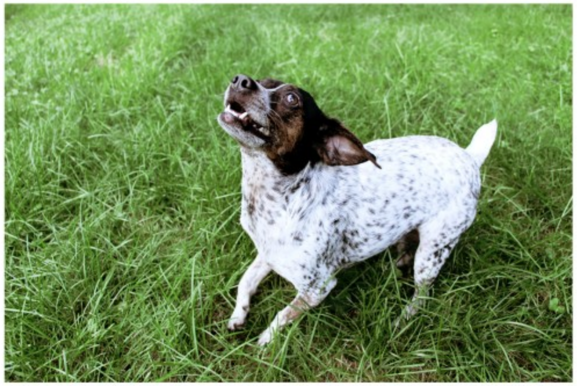
{terrier}



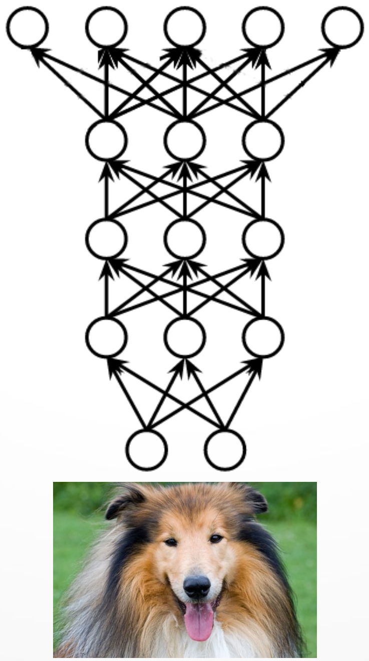
Single-Task Learning

{rottweiler}

{collie}



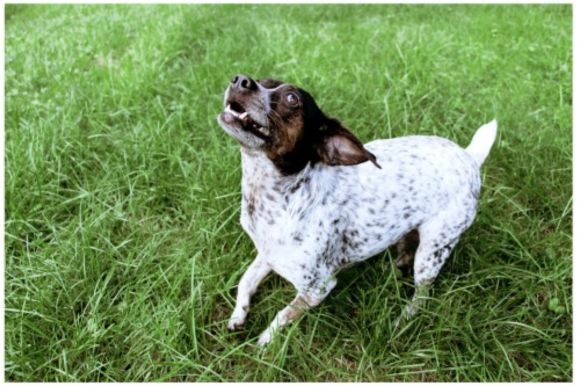
{terrier}



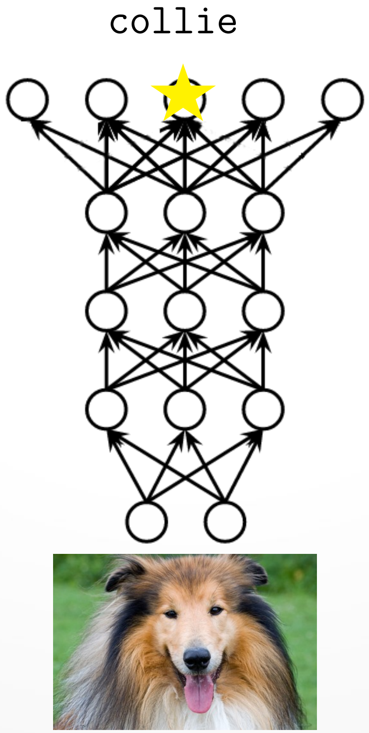
Single-Task Learning

{rottweiler}

{collie}



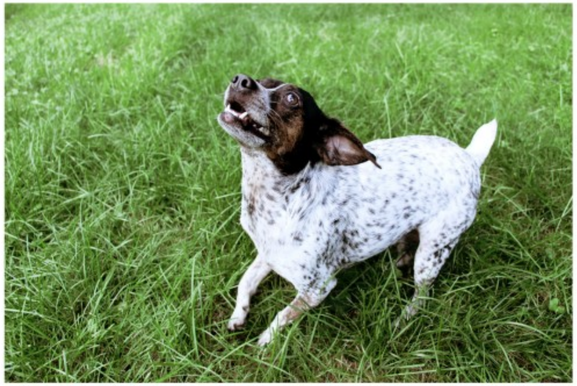
{terrier}



Multi-Task Learning

{rottweiler, large}

{collie, large}

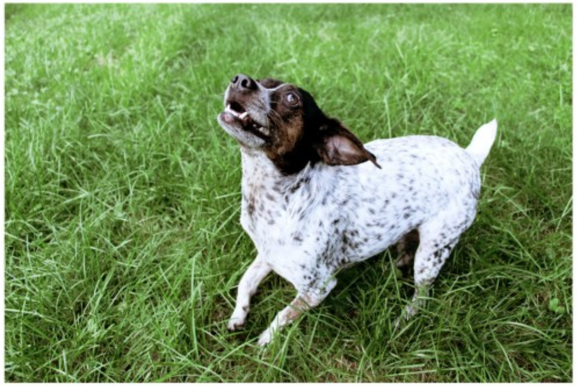


{terrier, small}

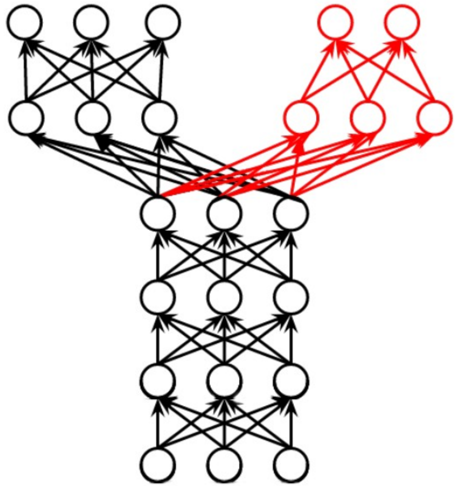
Multi-Task Learning

{rottweiler, large}

{collie, large}



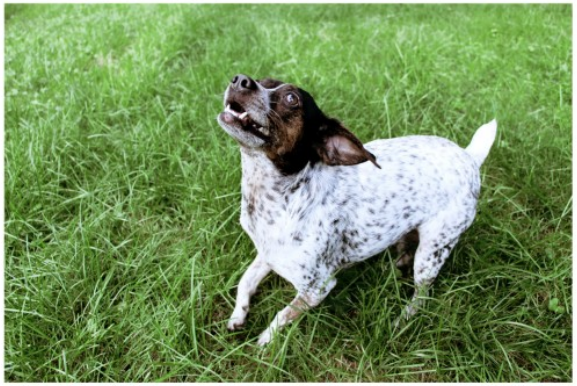
{terrier, small}



Multi-Task Learning

{rottweiler, large}

{collie, large}



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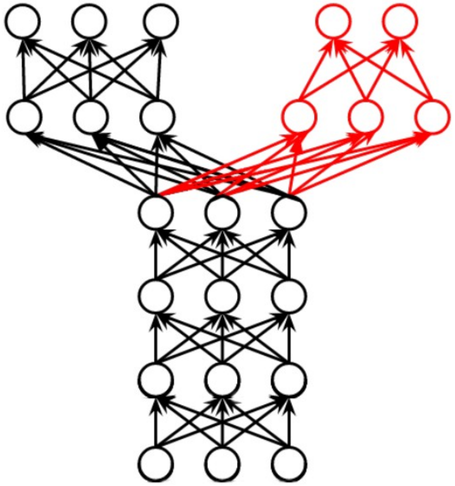
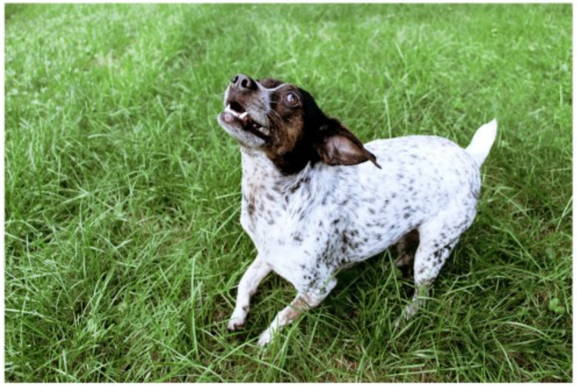


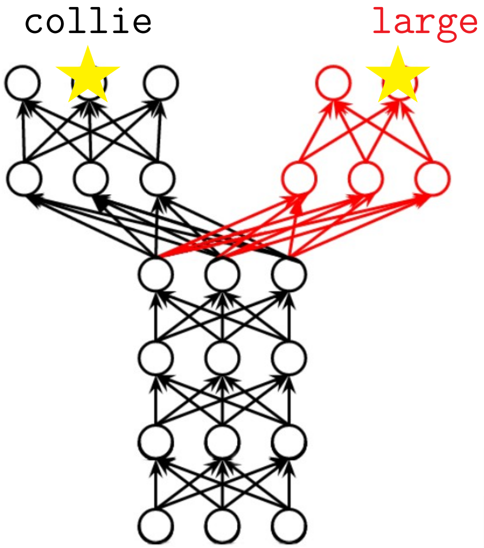
Multi-Task Learning

{rottweiler, large}

{collie, large}



{terrier, small}



Multi-Task Studies

Linguist-Crafted Tasks

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Can Linguistics help in a MTL Framework?

Linguist-Crafted Tasks

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- **Yes**: Bells and Renals (2015), Huang et al. (2015), Chen & Mak (2015), Seltzer & Droppo (2013)

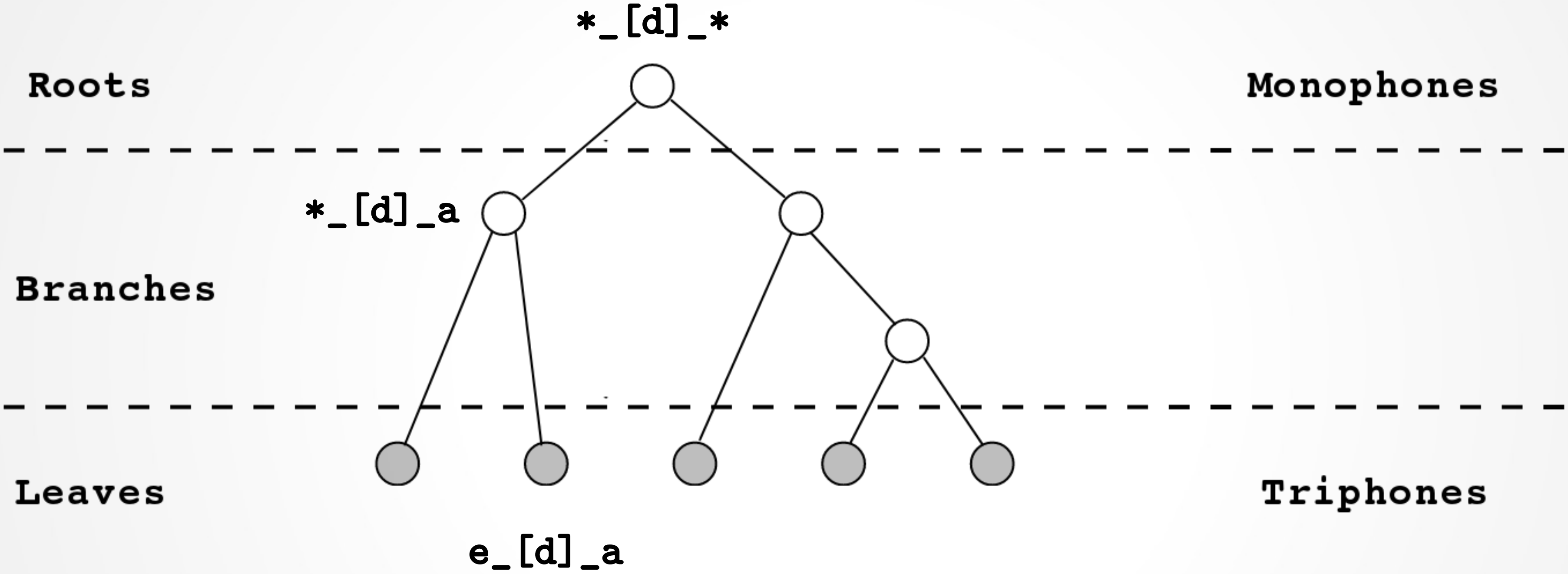
Linguist-Crafted Tasks

Can Linguistics help in a MTL Framework?

- **Yes**: Bells and Renals (2015), Huang et al. (2015), Chen & Mak (2015), Seltzer & Droppo (2013) ...
- **No**: Pironkov et al (2016)

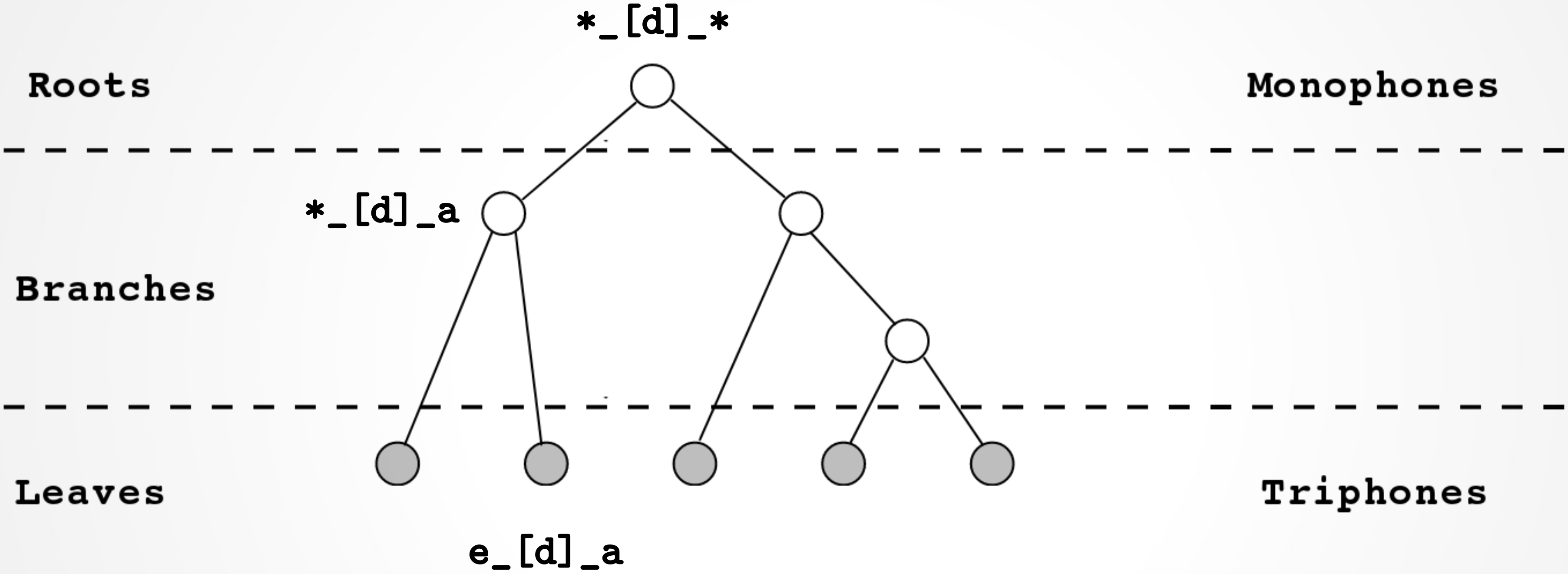
“Using even broader phonetic classes (such as plosive, fricative, nasal...) is not efficient for MTL speech recognition.”

Linguist-Crafted Tasks

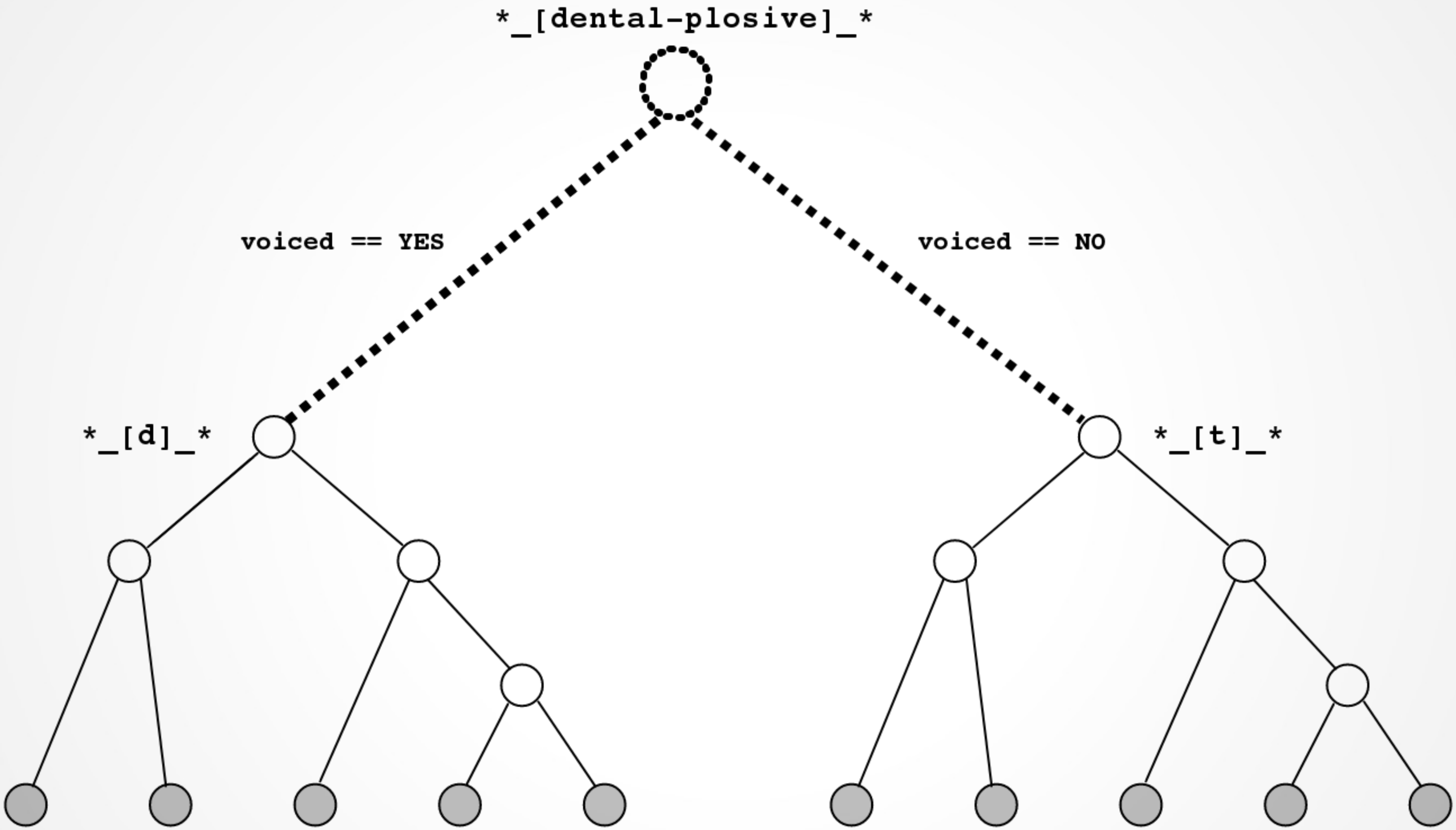


Linguist-Crafted Tasks

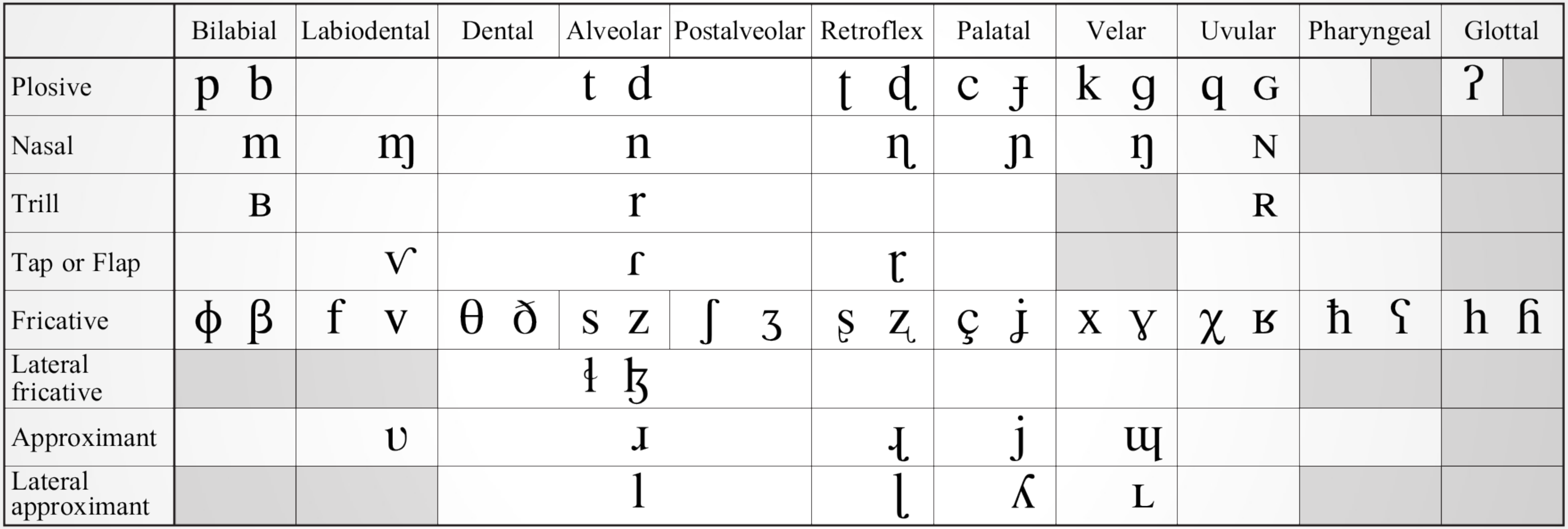
Deeper roots!



Linguist-Crafted Tasks



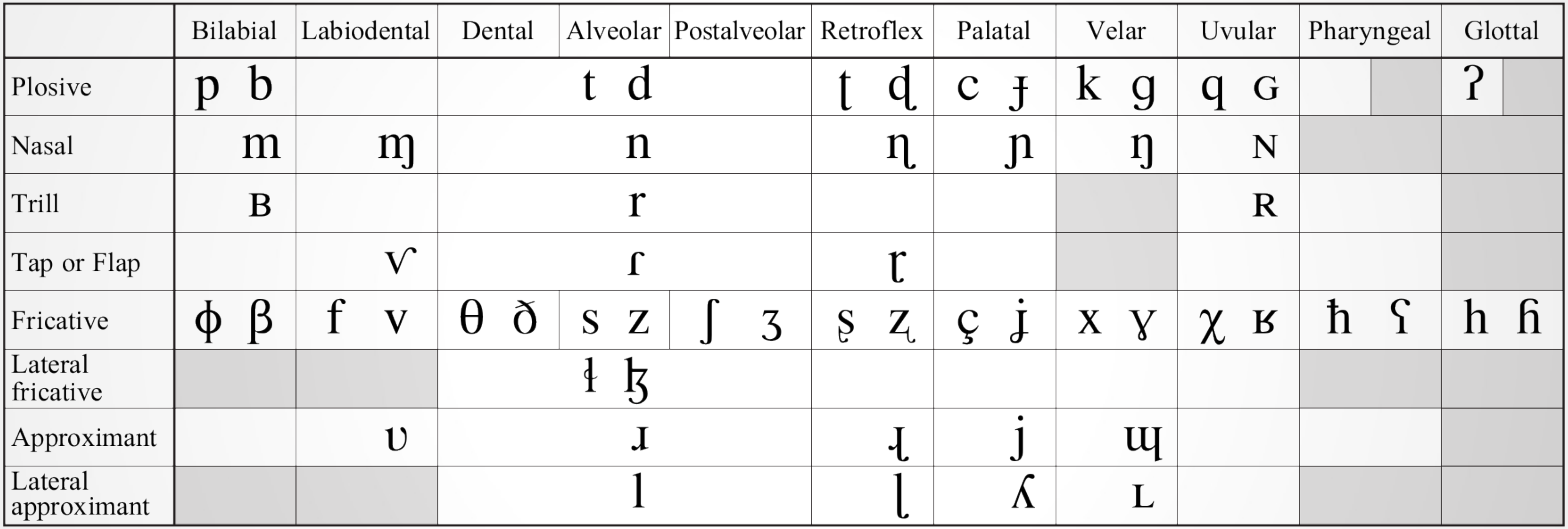
Linguistic Knowledge



	Bilabial	Labiodental	Dental	Alveolar	Postalveolar	Retroflex	Palatal	Velar	Uvular	Pharyngeal	Glottal
Plosive	p b			t d		ʈ ɖ	c ɟ	k ɡ	q ɢ		ʔ
Nasal	m	ɱ		n		ɳ	ɲ	ŋ	ɴ		
Trill	ʙ			r					ʀ		
Tap or Flap		ⱱ		ɾ		ɽ					
Fricative	ɸ β	f v	θ ð	s z	ʃ ʒ	ʂ ʐ	ç ʝ	x ɣ	χ ʁ	ħ ʕ	h ɦ
Lateral fricative				ɬ ɮ							
Approximant		ʋ		ɹ		ɻ	j	ɰ			
Lateral approximant				l		ɭ	ʎ	ʟ			

Linguistic Knowledge

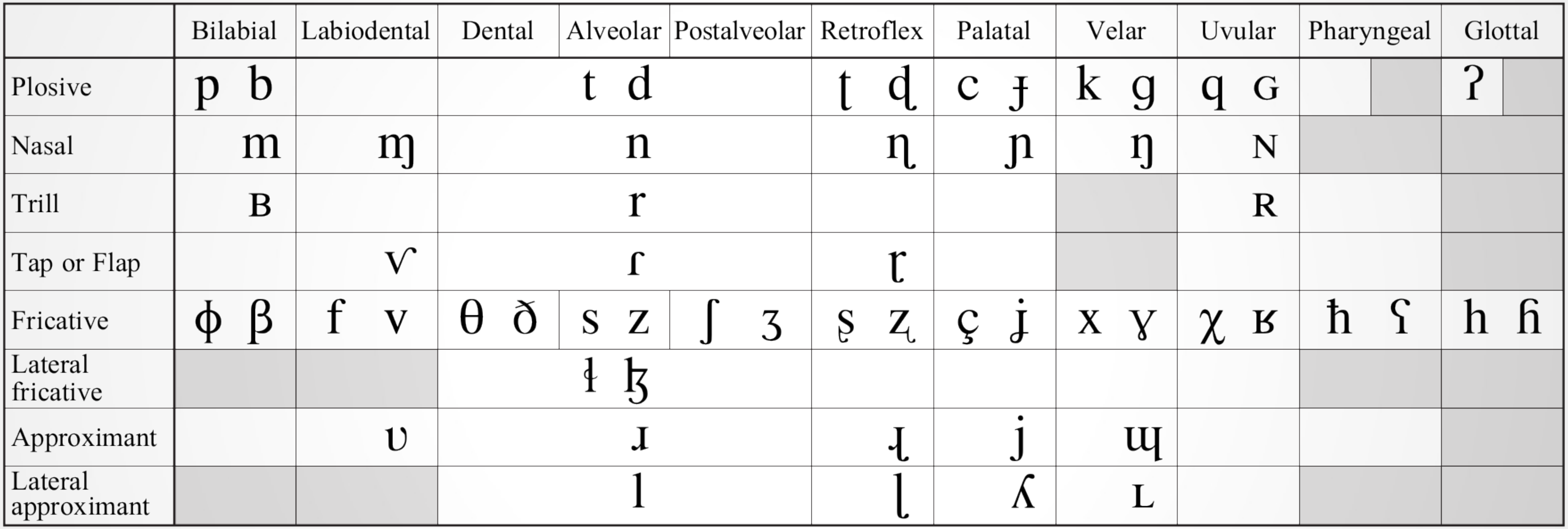
Rows == Manner



	Bilabial	Labiodental	Dental	Alveolar	Postalveolar	Retroflex	Palatal	Velar	Uvular	Pharyngeal	Glottal
Plosive	p b			t d		ʈ ɖ	c ɟ	k g	q ɢ		ʔ
Nasal	m	ɱ		n		ɳ	ɲ	ŋ	ɴ		
Trill	ʙ			r					ʀ		
Tap or Flap		ⱱ		ɾ		ɽ					
Fricative	ɸ β	f v	θ ð	s z	ʃ ʒ	ʂ ʐ	ç ʝ	x ɣ	χ ʁ	ħ ʕ	h ɦ
Lateral fricative				ɬ ɮ							
Approximant		ʋ		ɹ		ɻ	j	ɰ			
Lateral approximant				l		ɭ	ʎ	ʟ			

Linguistic Knowledge

Rows == Manner   Columns == Place

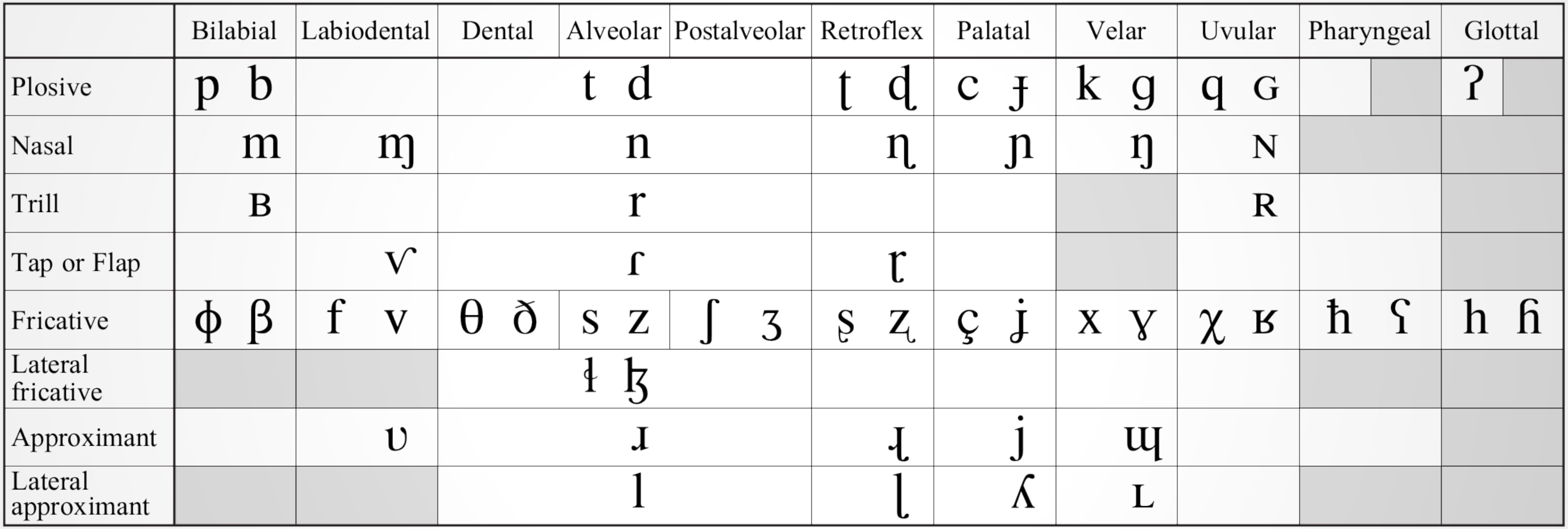


	Bilabial	Labiodental	Dental	Alveolar	Postalveolar	Retroflex	Palatal	Velar	Uvular	Pharyngeal	Glottal
Plosive	p b			t d		ʈ ɖ	c ɟ	k g	q ɢ		ʔ
Nasal	m	ɱ		n		ɳ	ɲ	ŋ	ɴ		
Trill	ʙ			r					ʀ		
Tap or Flap		ⱱ		ɾ		ɽ					
Fricative	ɸ β	f v	θ ð	s z	ʃ ʒ	ʂ ʐ	ç ʝ	x ɣ	χ ʁ	ħ ʕ	h ɦ
Lateral fricative				ɬ ɮ							
Approximant		ʋ		ɹ		ɻ	j	ɰ			
Lateral approximant				l		ɭ	ʎ	ʟ			

Linguistic Knowledge

Rows == Manner

Columns == Place

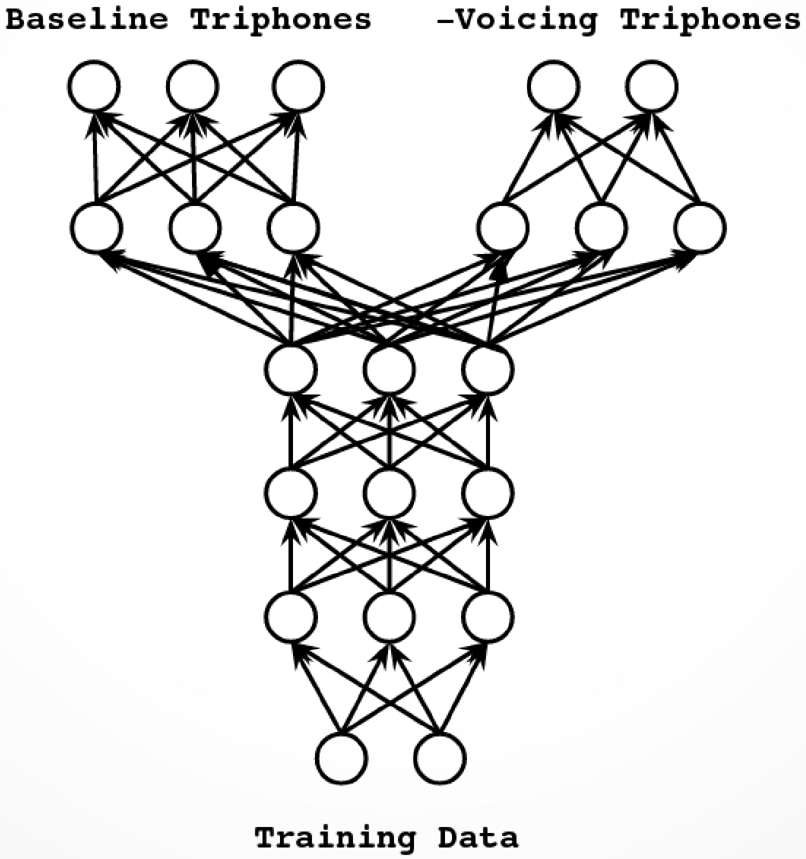


	Bilabial	Labiodental	Dental	Alveolar	Postalveolar	Retroflex	Palatal	Velar	Uvular	Pharyngeal	Glottal
Plosive	p b			t d		ʈ ɖ	c ɟ	k ɡ	q ɢ		ʔ
Nasal	m	ɱ		n		ɳ	ɲ	ŋ	ɴ		
Trill	ʙ			r					ʀ		
Tap or Flap		ⱱ		ɾ		ɽ					
Fricative	ɸ β	f v	θ ð	s z	ʃ ʒ	ʂ ʐ	ç ʝ	x ɣ	χ ʁ	ħ ʕ	h ɦ
Lateral fricative				ɬ ɮ							
Approximant		ʋ		ɹ		ɻ	j	ɰ			
Lateral approximant				l		ɭ	ʎ	ʟ			

Cells == Voicing

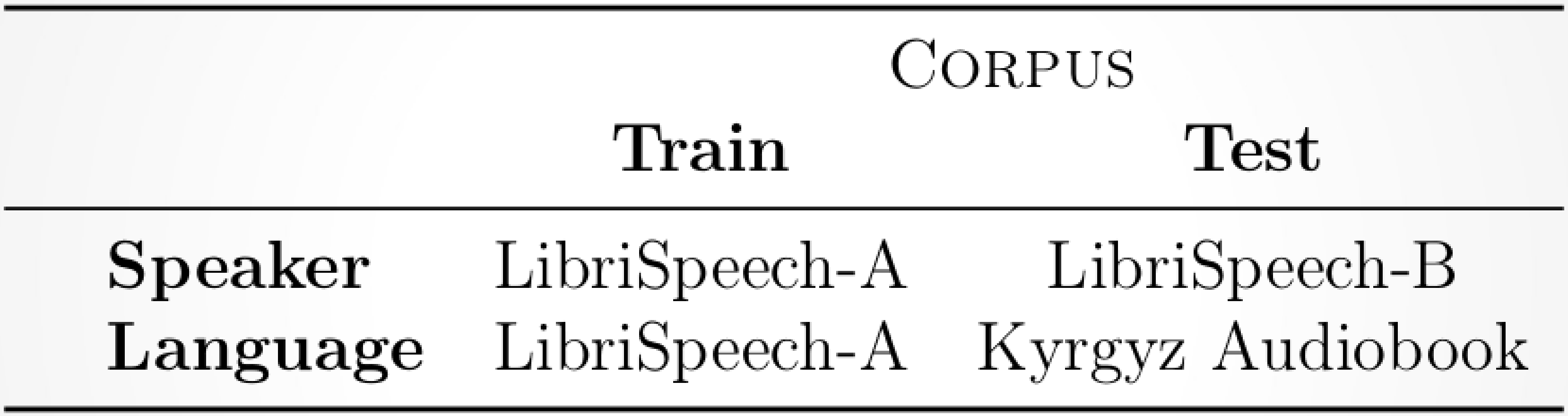
Linguistic Knowledge

Example: Collapsing on Voice



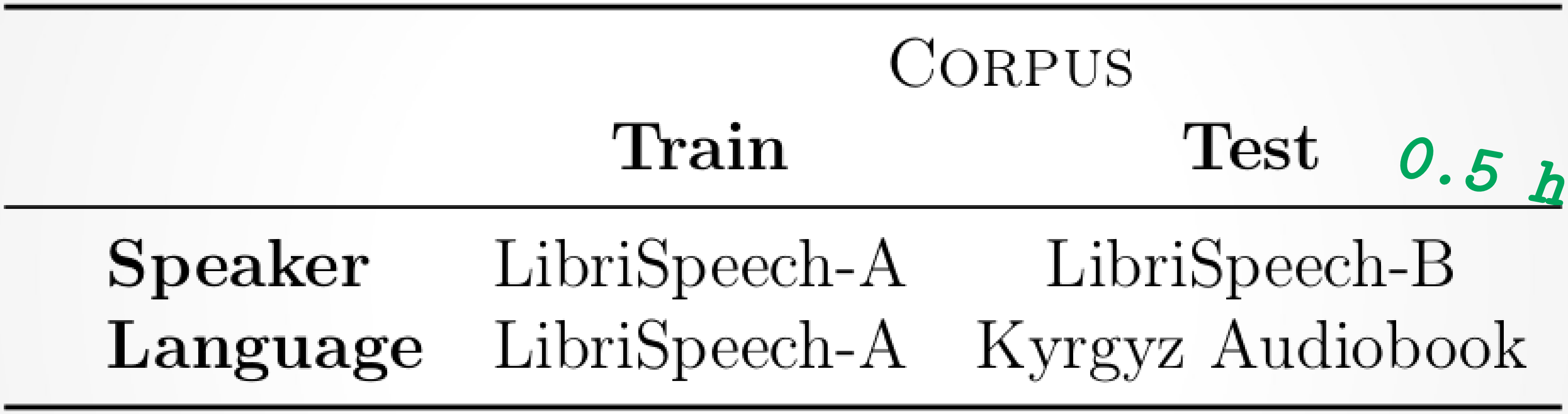
Methods

Data



	Corpus	
	Train	**Test**
Speaker	LibriSpeech-A	LibriSpeech-B
Language	LibriSpeech-A	Kyrgyz Audiobook

Data

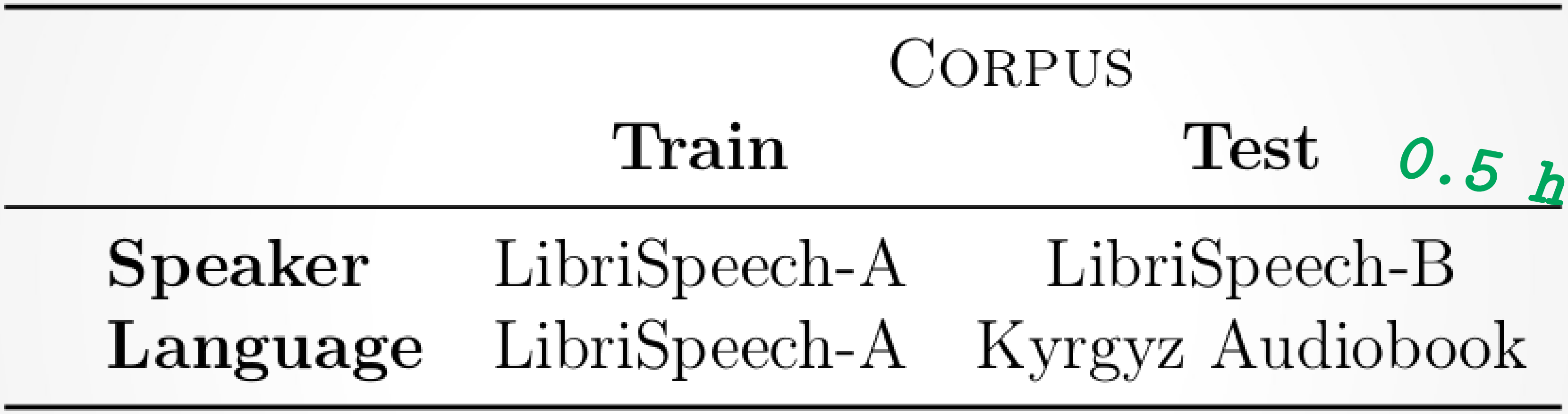


	Corpus	
	Train	**Test**
Speaker	LibriSpeech-A	LibriSpeech-B
Language	LibriSpeech-A	Kyrgyz Audiobook

0.5 hours

4.86 hours

Data



	Corpus	
	Train	**Test**
Speaker	LibriSpeech-A	LibriSpeech-B
Language	LibriSpeech-A	Kyrgyz Audiobook

0.5 hours

4.86 hours

1.6 hours

Alignment Procedure

- GMM-HMM Alignment

- Monophones
  - 25 iterations of Baum-Welch
  - 1,000 Gaussian components

- Triphones
  - 25 iterations of Baum-Welch
  - 1,000 leaves
  - 2,000 Gaussian components

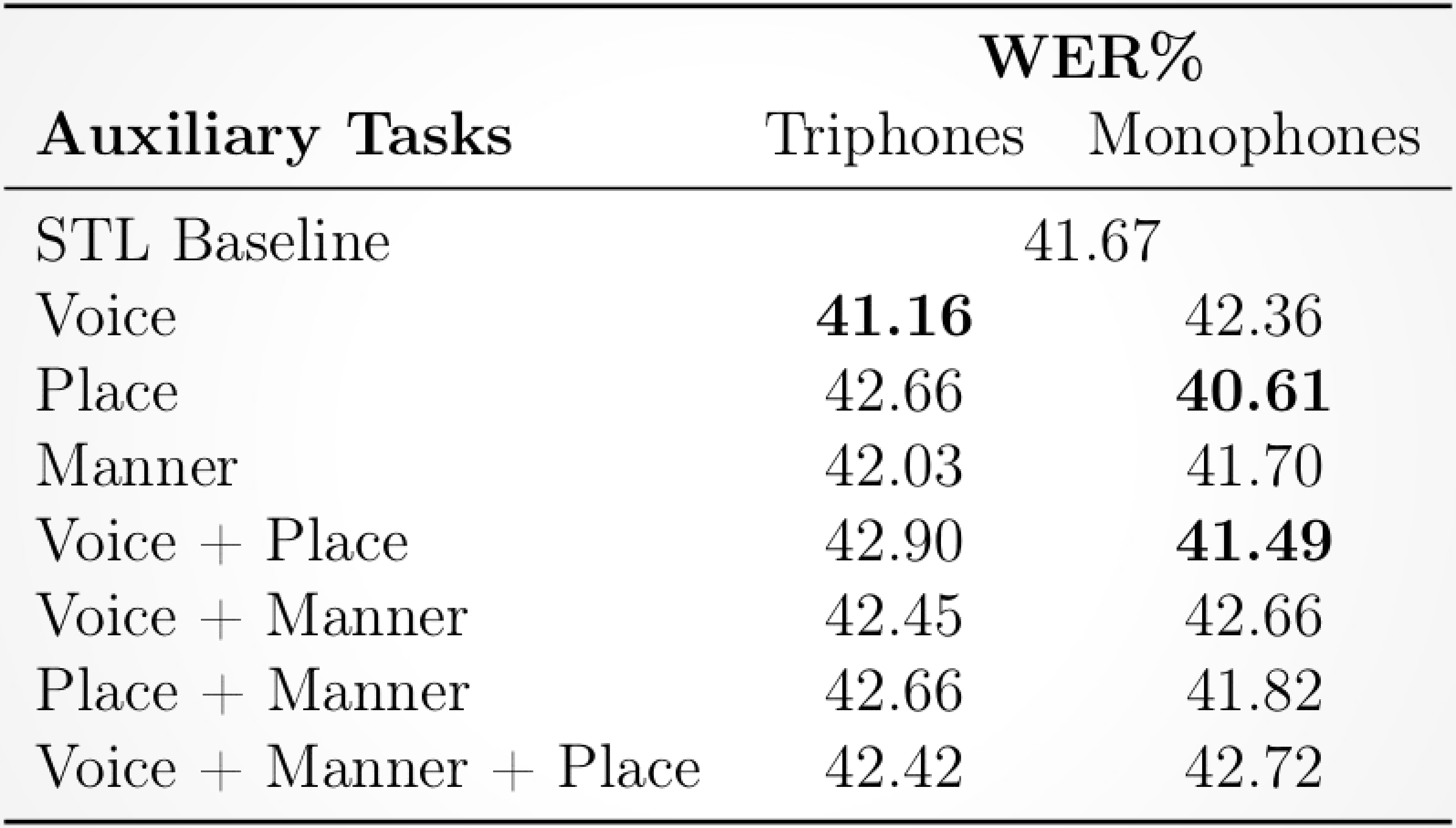
DNN Training Procedure

- 5 Layer, Time-Delay Neural Network
- 500 Nodes / Layer
- ReLU Activations
- Stochastic Gradient Descent for 2 epochs

Monolingual Experiments

	Corpus	
	Train	**Test**
Speaker	LibriSpeech-A	LibriSpeech-B
Language	LibriSpeech-A	Kyrgyz Audiobook

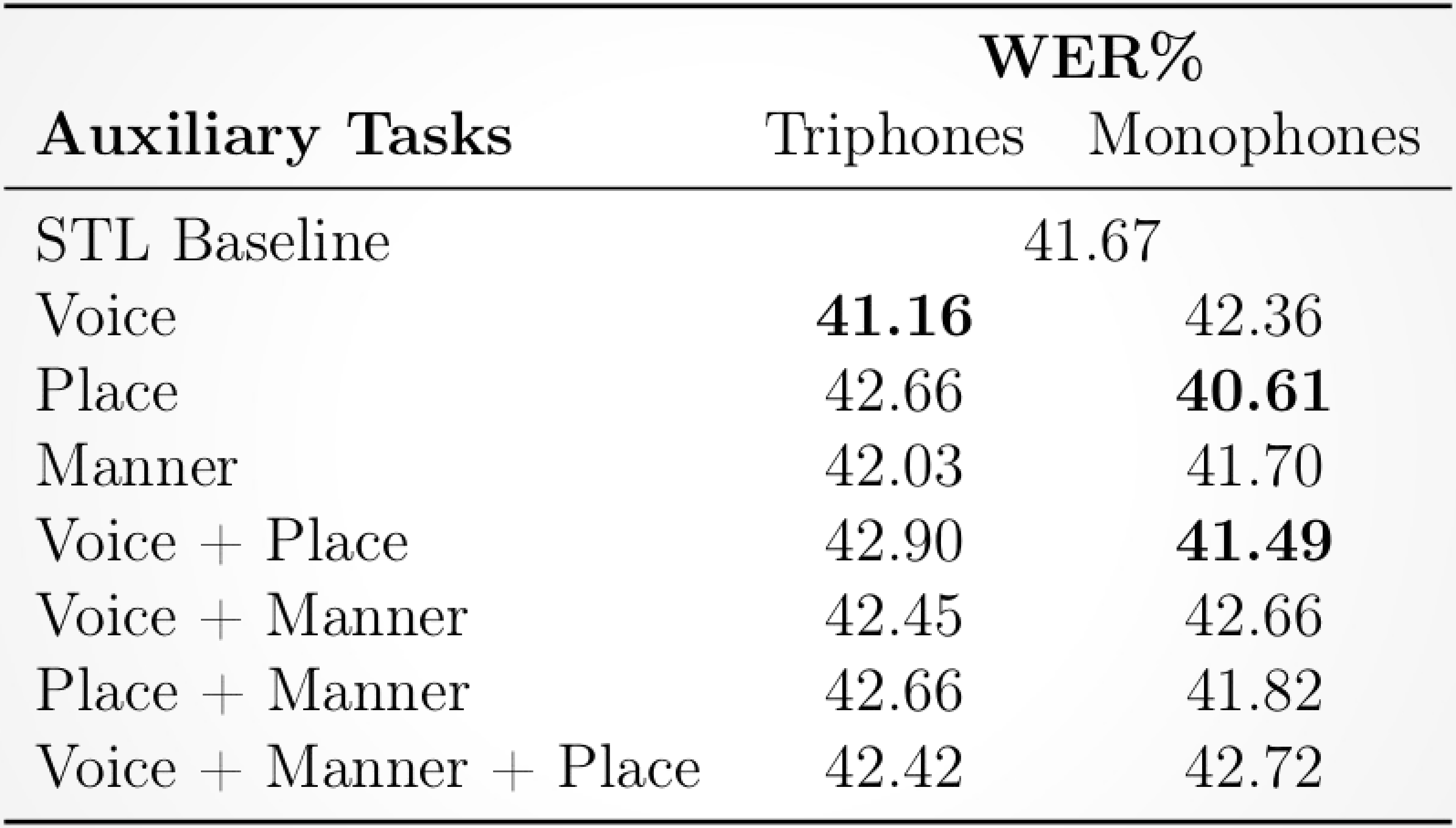
Monolingual Experiments



	WER%	
Auxiliary Tasks	Triphones	Monophones
STL Baseline	41.67	
Voice	**41.16**	42.36
Place	42.66	**40.61**
Manner	42.03	41.70
Voice + Place	42.90	**41.49**
Voice + Manner	42.45	42.66
Place + Manner	42.66	41.82
Voice + Manner + Place	42.42	42.72

Monolingual Experiments

Not so great :(



	WER%	
Auxiliary Tasks	Triphones	Monophones
STL Baseline	41.67	
Voice	**41.16**	42.36
Place	42.66	**40.61**
Manner	42.03	41.70
Voice + Place	42.90	**41.49**
Voice + Manner	42.45	42.66
Place + Manner	42.66	41.82
Voice + Manner + Place	42.42	42.72

Monolingual Experiments

The **main** task is **more** important...

Monolingual Experiments

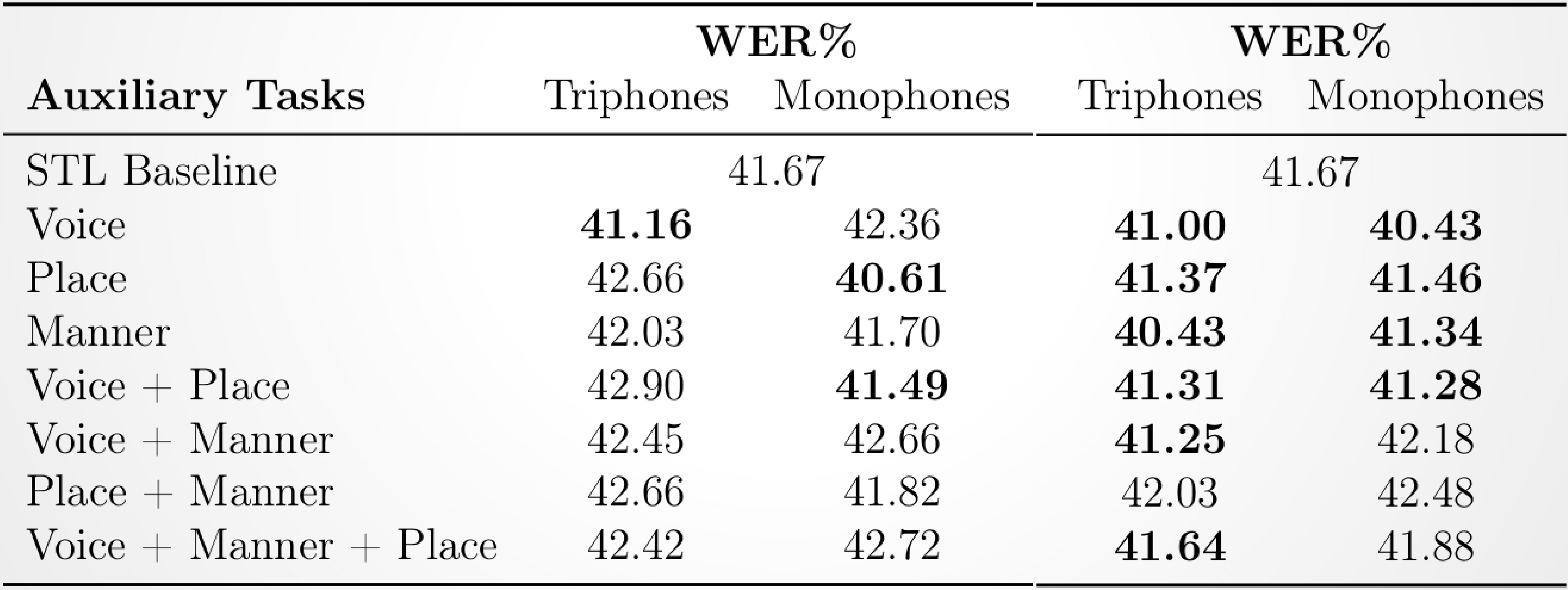
The **main** task is **more** important...

Implement a relative **weighting**!

Monolingual Experiments

Source:Target Weighting

1:1 **1/3:1**



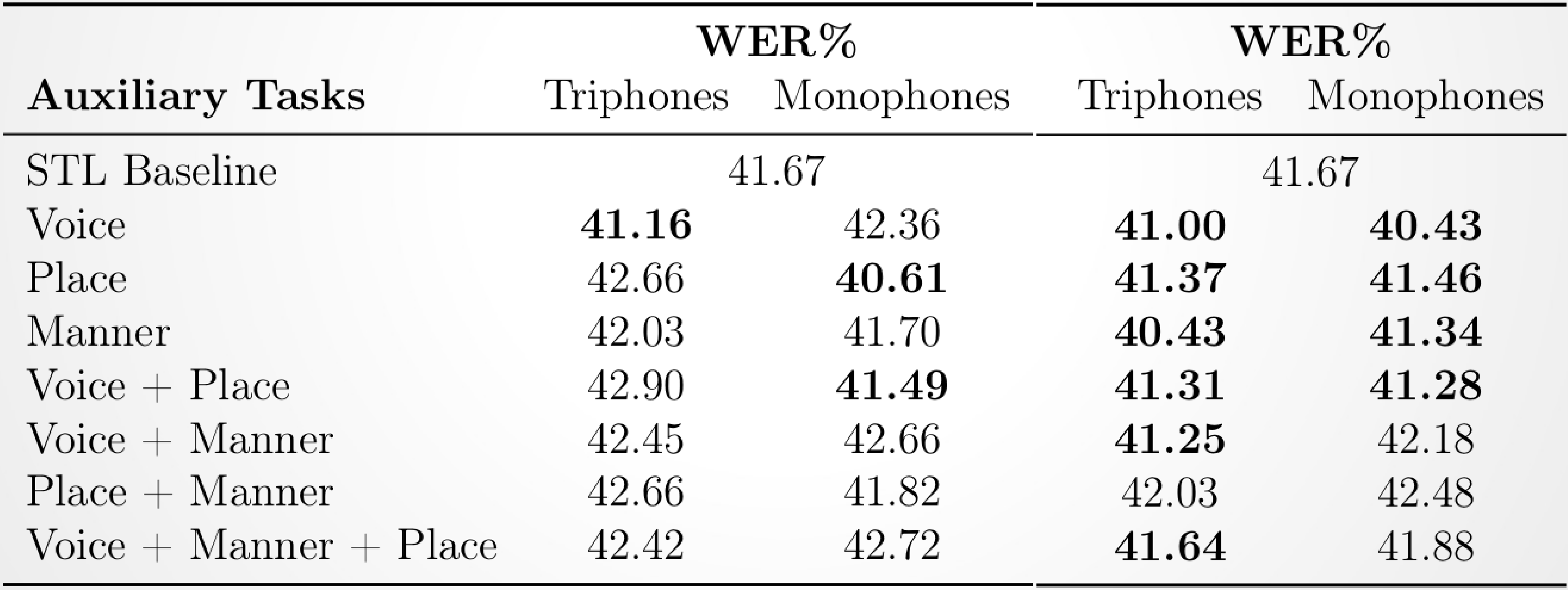
	WER%		**WER%**	
Auxiliary Tasks	Triphones	Monophones	Triphones	Monophones
STL Baseline	41.67		41.67	
Voice	**41.16**	42.36	**41.00**	**40.43**
Place	42.66	**40.61**	**41.37**	**41.46**
Manner	42.03	41.70	**40.43**	**41.34**
Voice + Place	42.90	**41.49**	**41.31**	**41.28**
Voice + Manner	42.45	42.66	**41.25**	42.18
Place + Manner	42.66	41.82	42.03	42.48
Voice + Manner + Place	42.42	42.72	**41.64**	41.88

Monolingual Experiments

Now, that looks better :)

Source:Target Weighting

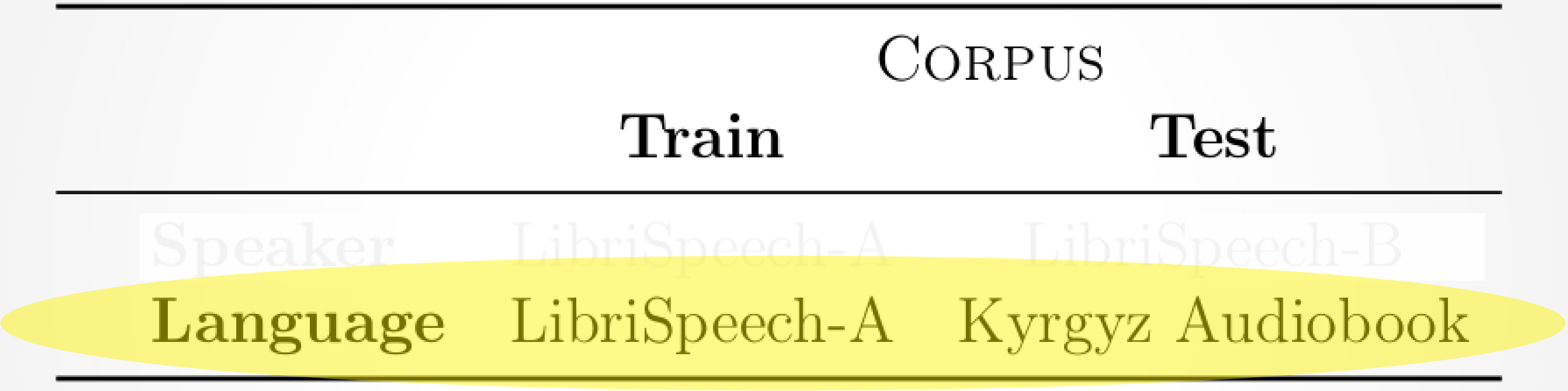
1:1 **1/3:1**



	WER%		**WER%**	
Auxiliary Tasks	Triphones	Monophones	Triphones	Monophones
STL Baseline	41.67		41.67	
Voice	**41.16**	42.36	**41.00**	**40.43**
Place	42.66	**40.61**	**41.37**	**41.46**
Manner	42.03	41.70	**40.43**	**41.34**
Voice + Place	42.90	**41.49**	**41.31**	**41.28**
Voice + Manner	42.45	42.66	**41.25**	42.18
Place + Manner	42.66	41.82	42.03	42.48
Voice + Manner + Place	42.42	42.72	**41.64**	41.88

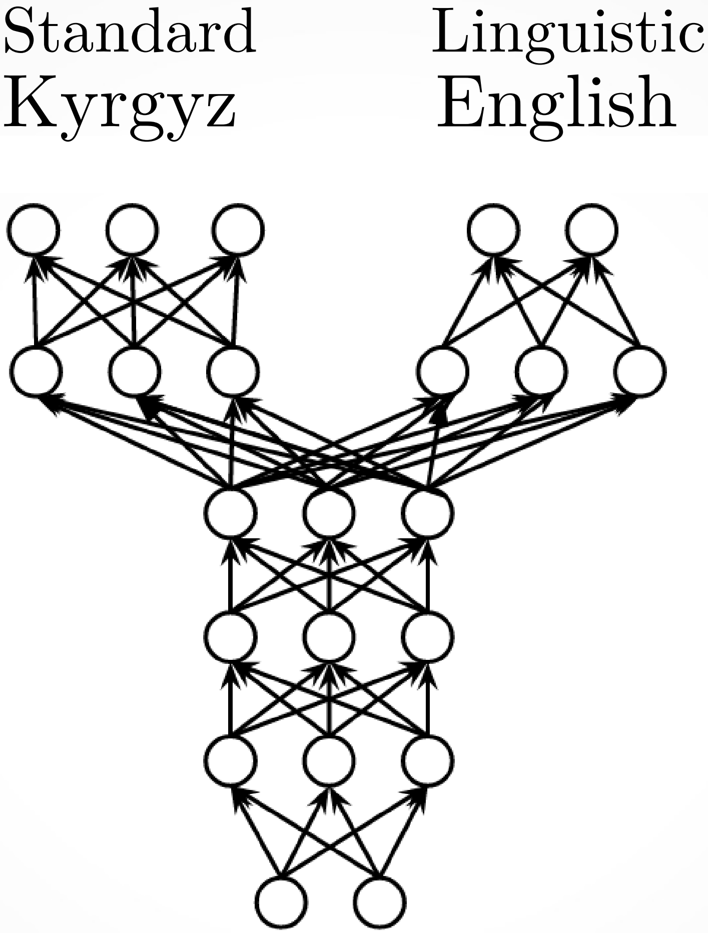
Multilingual Experiments

Multilingual Experiments



	Corpus	
	Train	**Test**
Speaker	LibriSpeech-A	LibriSpeech-B
Language	LibriSpeech-A	Kyrgyz Audiobook

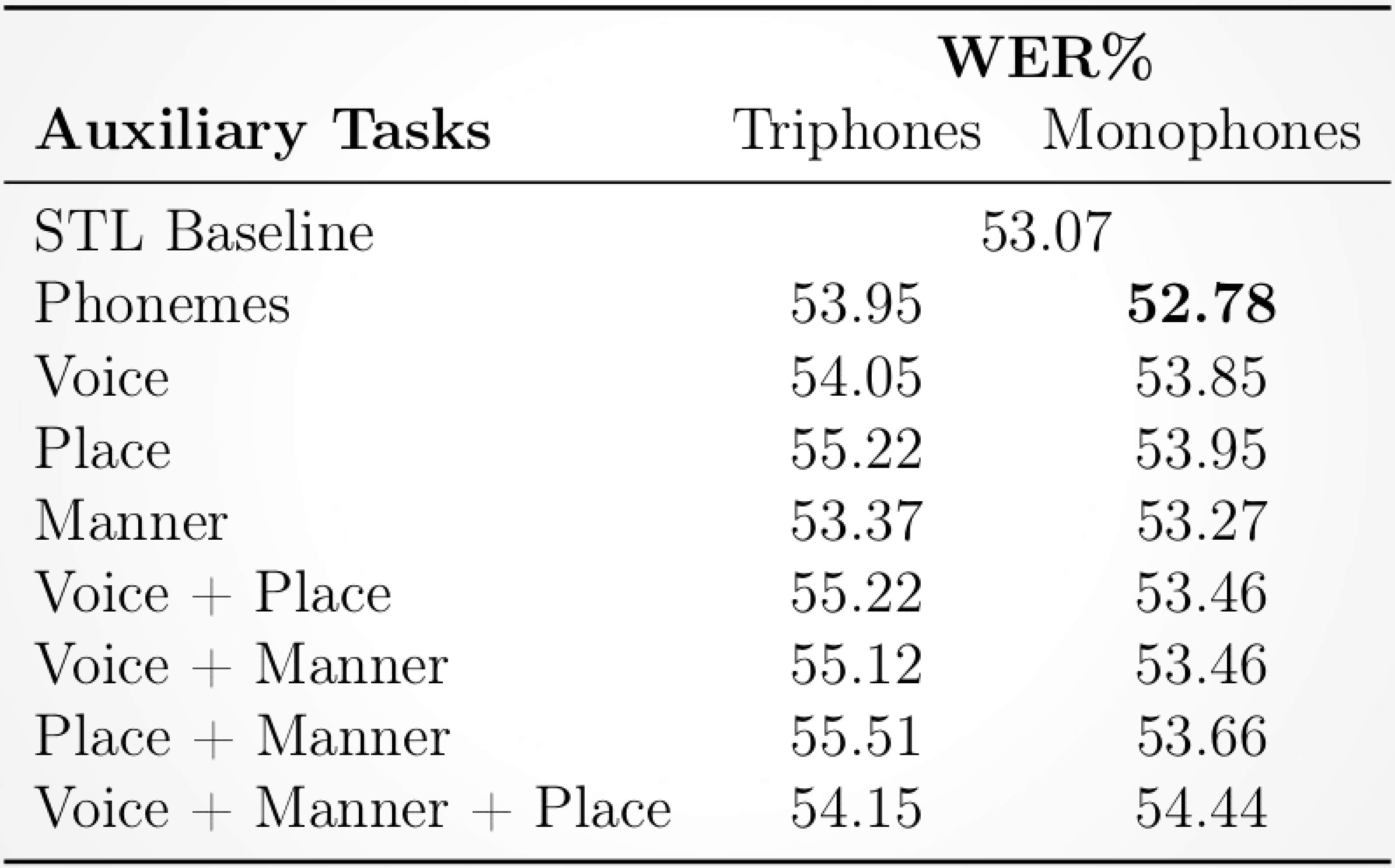
Multilingual Experiments



Standard Kyrgyz

Linguistic English

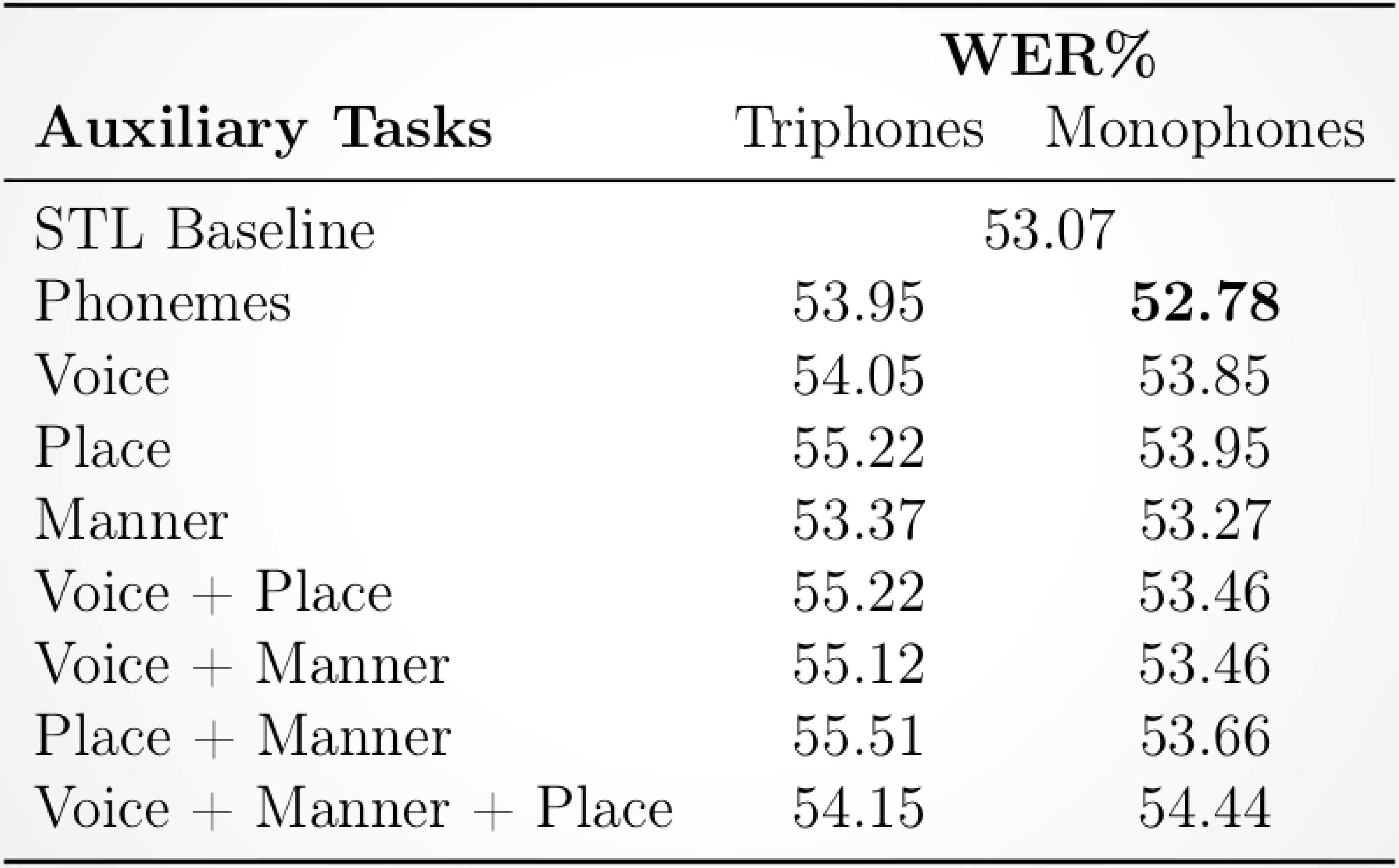
Multilingual Experiments



	WER%	
Auxiliary Tasks	Triphones	Monophones
STL Baseline	53.07	
Phonemes	53.95	**52.78**
Voice	54.05	53.85
Place	55.22	53.95
Manner	53.37	53.27
Voice + Place	55.22	53.46
Voice + Manner	55.12	53.46
Place + Manner	55.51	53.66
Voice + Manner + Place	54.15	54.44

Multilingual Experiments

Not so great :(



	WER%	
Auxiliary Tasks	Triphones	Monophones
STL Baseline	53.07	
Phonemes	53.95	**52.78**
Voice	54.05	53.85
Place	55.22	53.95
Manner	53.37	53.27
Voice + Place	55.22	53.46
Voice + Manner	55.12	53.46
Place + Manner	55.51	53.66
Voice + Manner + Place	54.15	54.44

Multilingual Experiments

Source:Target Weighting

	1:1		**1/3:1**	
	WER%		**WER%**	
Auxiliary Tasks	Triphones	Monophones	Triphones	Monophones
STL Baseline	53.07		53.07	
Phonemes	53.95	**52.78**	**51.80**	**51.61**
Voice	54.05	53.85	**52.39**	53.46
Place	55.22	53.95	**51.90**	**52.29**
Manner	53.37	53.27	**52.00**	**51.80**
Voice + Place	55.22	53.46	**52.68**	**52.78**
Voice + Manner	55.12	53.46	**51.22**	**51.32**
Place + Manner	55.51	53.66	**50.83**	53.66
Voice + Manner + Place	54.15	54.44	**52.78**	**52.39**

Multilingual Experiments

Now, that looks better :)

Source:Target Weighting

	1:1		1/3:1	
	WER%		**WER%**	
Auxiliary Tasks	Triphones	Monophones	Triphones	Monophones
STL Baseline	53.07		53.07	
Phonemes	53.95	**52.78**	**51.80**	**51.61**
Voice	54.05	53.85	**52.39**	53.46
Place	55.22	53.95	**51.90**	**52.29**
Manner	53.37	53.27	**52.00**	**51.80**
Voice + Place	55.22	53.46	**52.68**	**52.78**
Voice + Manner	55.12	53.46	**51.22**	**51.32**
Place + Manner	55.51	53.66	**50.83**	53.66
Voice + Manner + Place	54.15	54.44	**52.78**	**52.39**

Summary: Linguistic Tasks

- Linguistics **can** help for transfer!
  - But we must keep in mind weighting
- More Tasks isn't always better
  - Monolingual: 1 extra task is best
  - Multilingual: 2 extra tasks is best

Engineered Tasks

Engineered Tasks

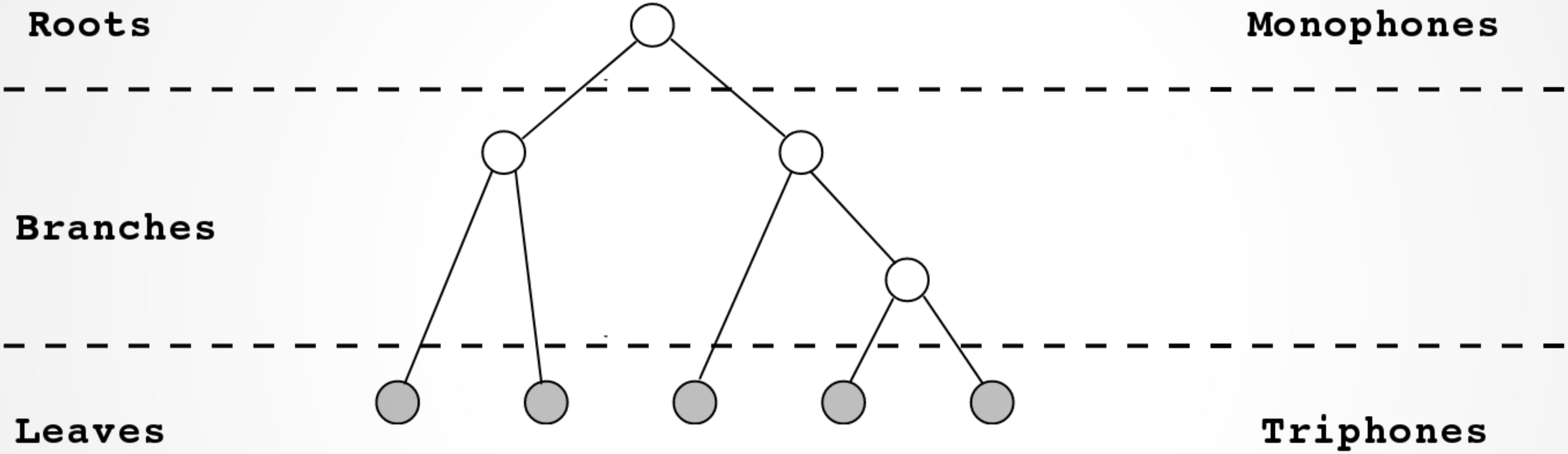
Can we find useful linguistic bias
without a linguist?

Engineered Tasks

Can we find useful linguistic bias **without** a linguist?

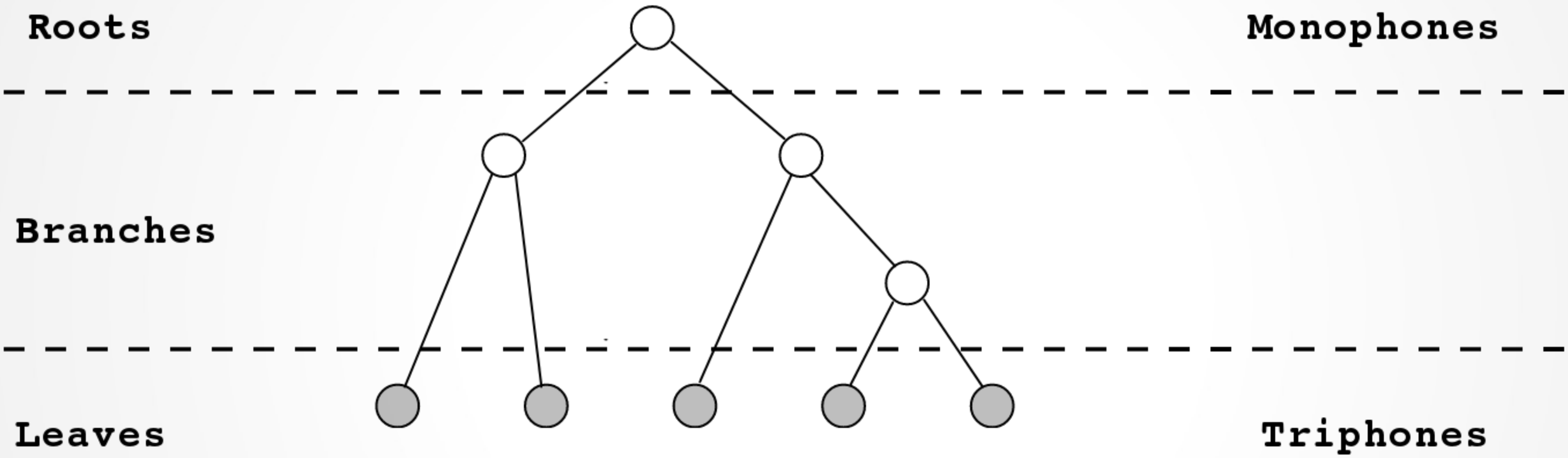
Focus on multilingual scenario

Linguist-Crafted Tasks



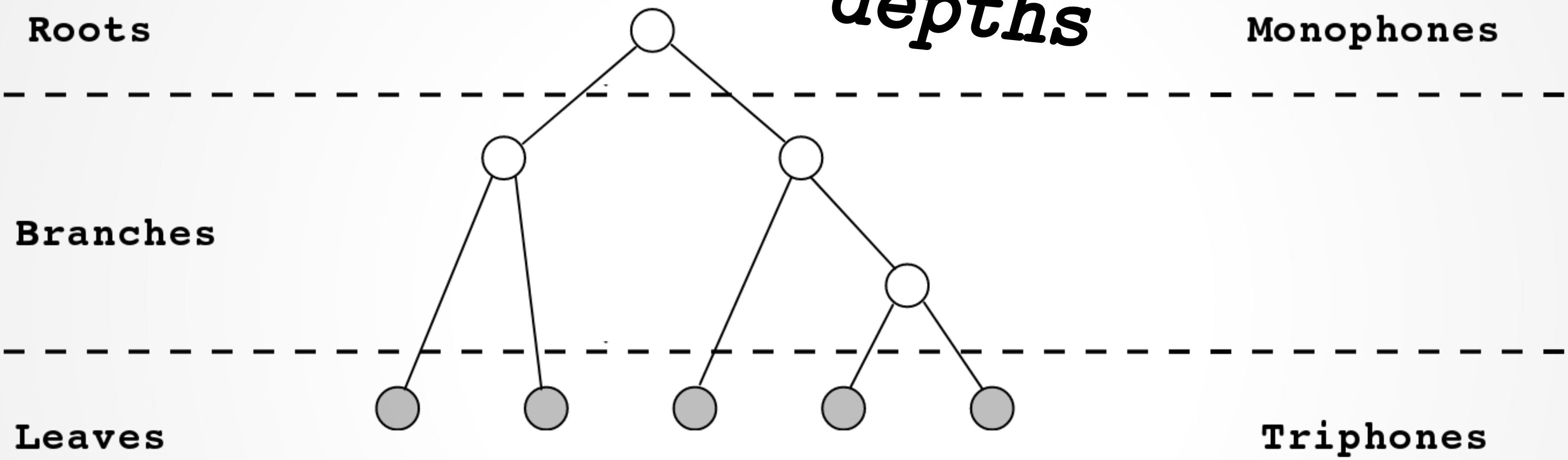
Linguist-Crafted Tasks

Lots of unused structure…



Linguist-Crafted Tasks

We can slice the tree at varying depths



Roots

Monophones

Branches

Leaves

Triphones

Alignment Procedure

- GMM-HMM Alignment

- Monophones
  - 25 iterations of Baum-Welch
  - 1,000 Gaussian components

- “Half-phones”
  - 25 iterations of Baum-Welch
  - 792 leaves
  - 5,000 Gaussian components

- Triphones
  - 25 iterations of Baum-Welch
  - 1584 leaves
  - 5,000 Gaussian components

Alignment Procedure

- GMM-HMM Alignment

- Monophones
  - 25 iterations of Baum-Welch
  - 1,000 Gaussian components

- "Half-phones" **(Half-way down the tree)**
  - 25 iterations of Baum-Welch
  - 792 leaves
  - 5,000 Gaussian components

- Triphones
  - 25 iterations of Baum-Welch
  - 1584 leaves
  - 5,000 Gaussian components

DNN Training Procedure

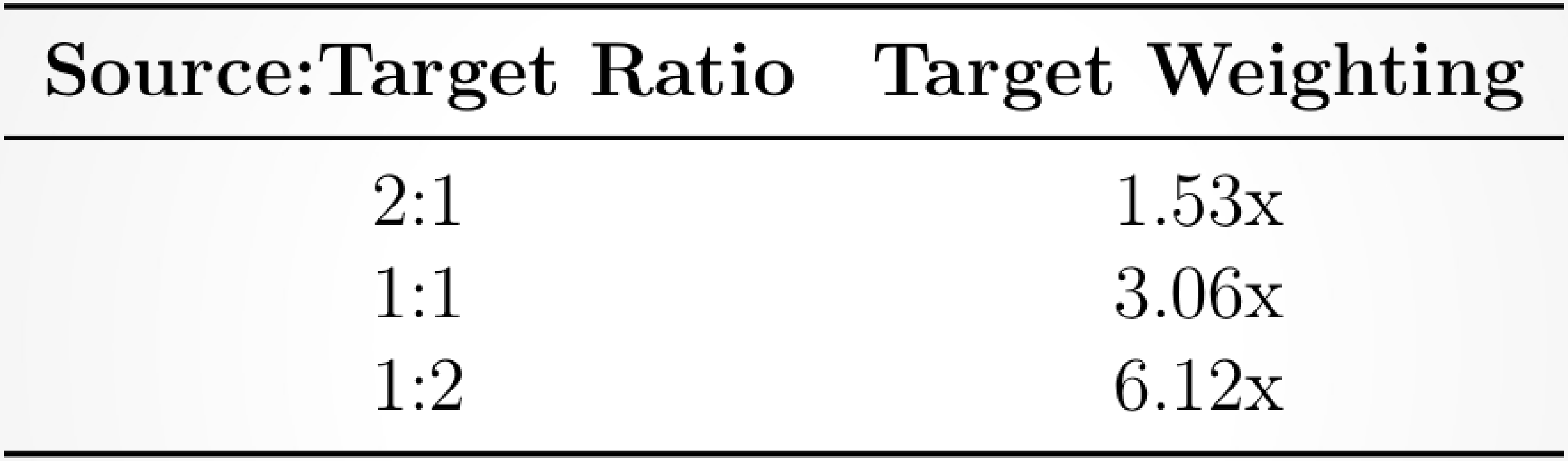
- 5 Layer, Time-Delay Neural Network
- 500 Nodes / Layer
- ReLU Activations
- Stochastic Gradient Descent for 10 epochs

DNN Training Procedure

Smarter weighting

DNN Training Procedure

Smarter weighting



Source:Target Ratio	Target Weighting
2:1	1.53x
1:1	3.06x
1:2	6.12x

Multilingual Engineered Tasks

	Corpus	
	Train	**Test**
Speaker	LibriSpeech-A	LibriSpeech-B
Language	LibriSpeech-A	Kyrgyz Audiobook

Multilingual Engineered Tasks

	Source:Target Weighting		
Auxiliary (Source Lang) Tasks	*1-to-2*	*1-to-1*	*2-to-1*
STL Baseline	50.54		
Monophones	**48.20**	**47.32**	**47.41**
Halfphones	**48.68**	**46.73**	**48.68**
Triphones	**49.37**	**47.12**	**46.73**
Monophones + Halfphones	**48.20**	**48.49**	**48.10**
Halfphones + Triphones	**50.05**	**48.00**	**47.90**
Monophones + Halfphones + Halfphones	**48.88**	**48.20**	**48.59**

Summary: Engineered Tasks

- Smarter Weighting helps
  - Based on size of datasets

- We **can** find tasks in the tree

- Again, more tasks isn’t always better

End-to-End Transfer Studies

Transfering Bias

Transfering Bias

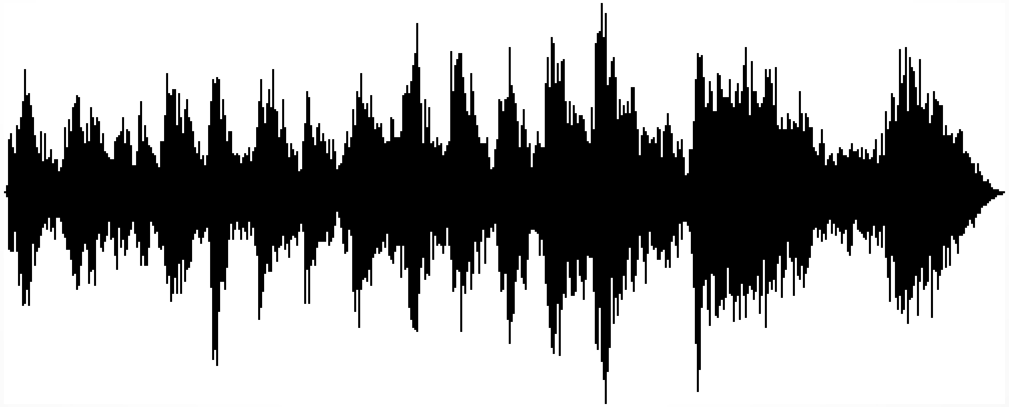
Bias Source	**Transfer Method**
source Dataset →	Multi-Task Learning
-or-	-or-
source Model →	Copy-Paste Transfer

End-to-end ASR

End-to-end ASR

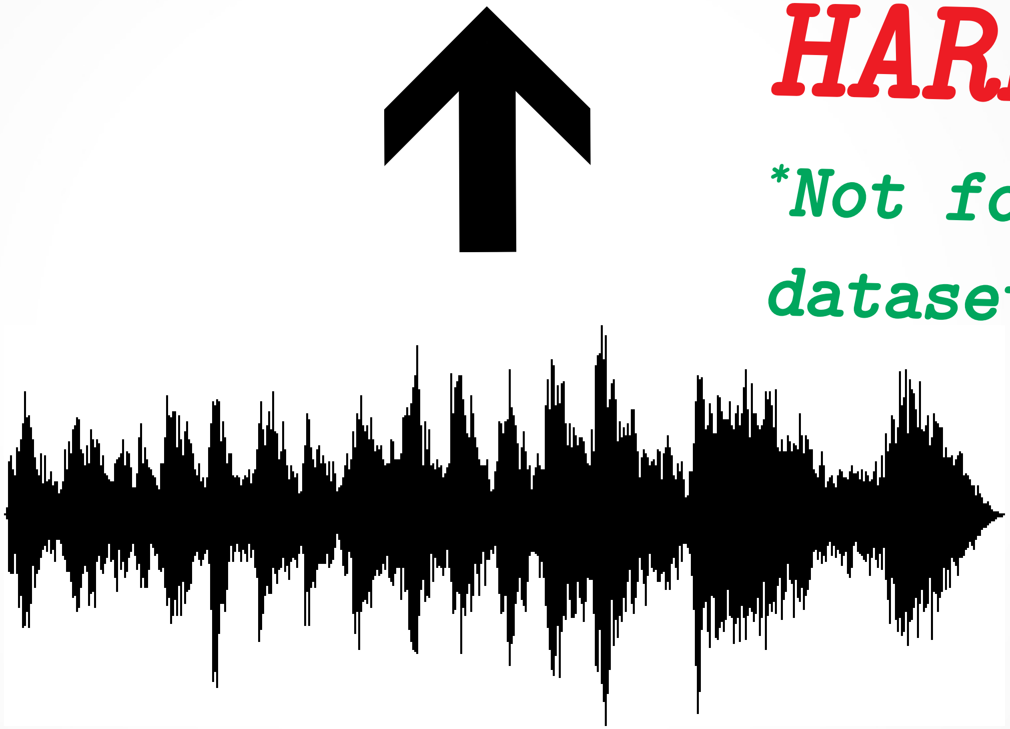
"THE DOG"

HARD



End-to-end ASR

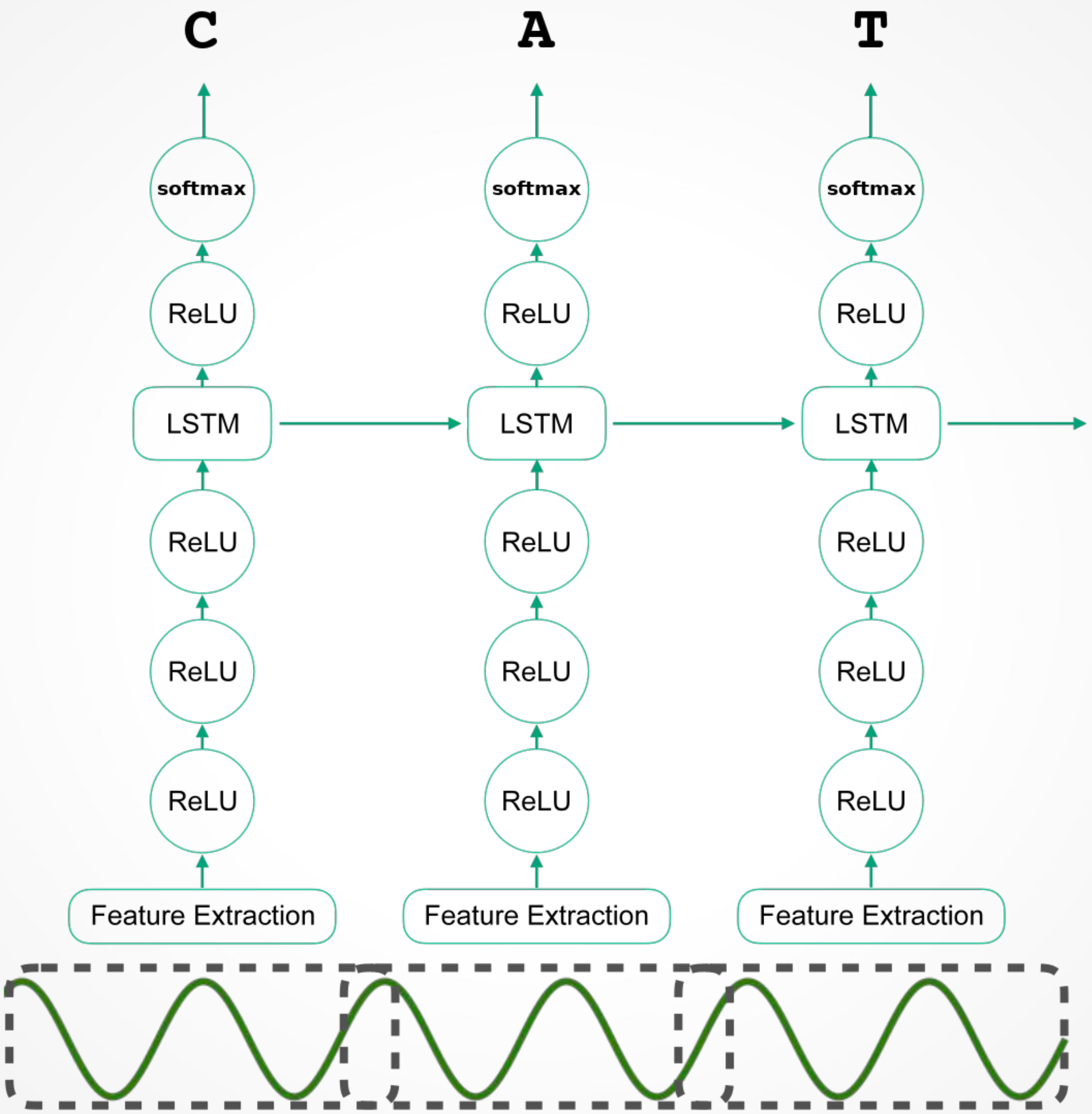
"THE DOG"



HARD*

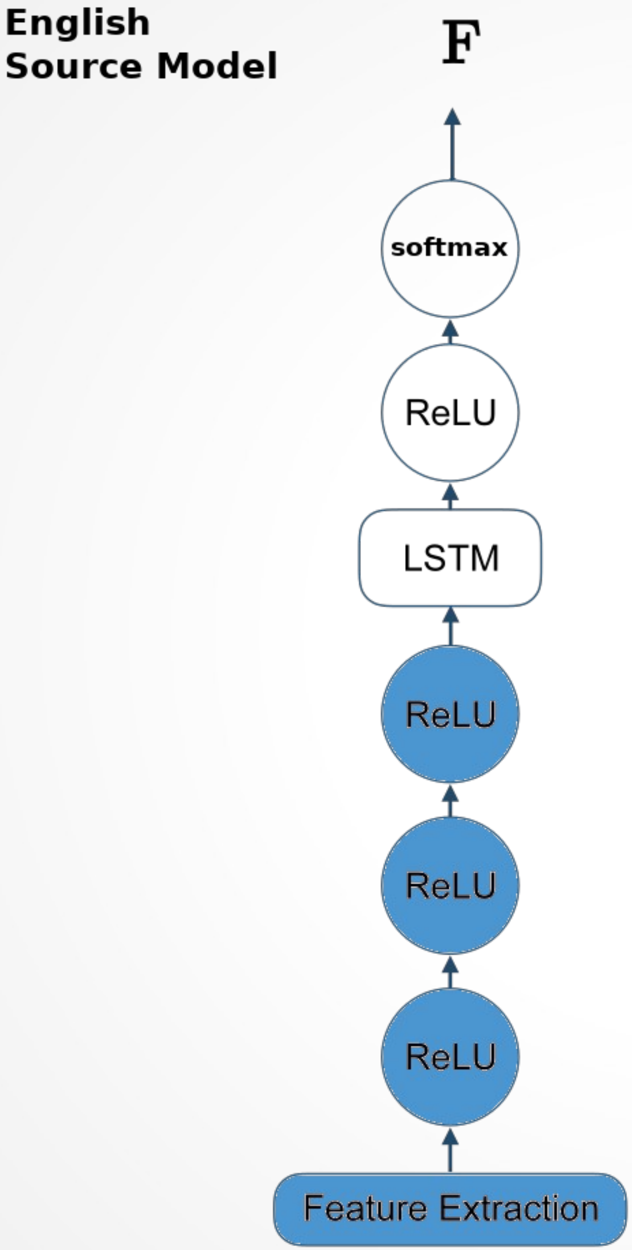
***Not for big datasets!**

DeepSpeech

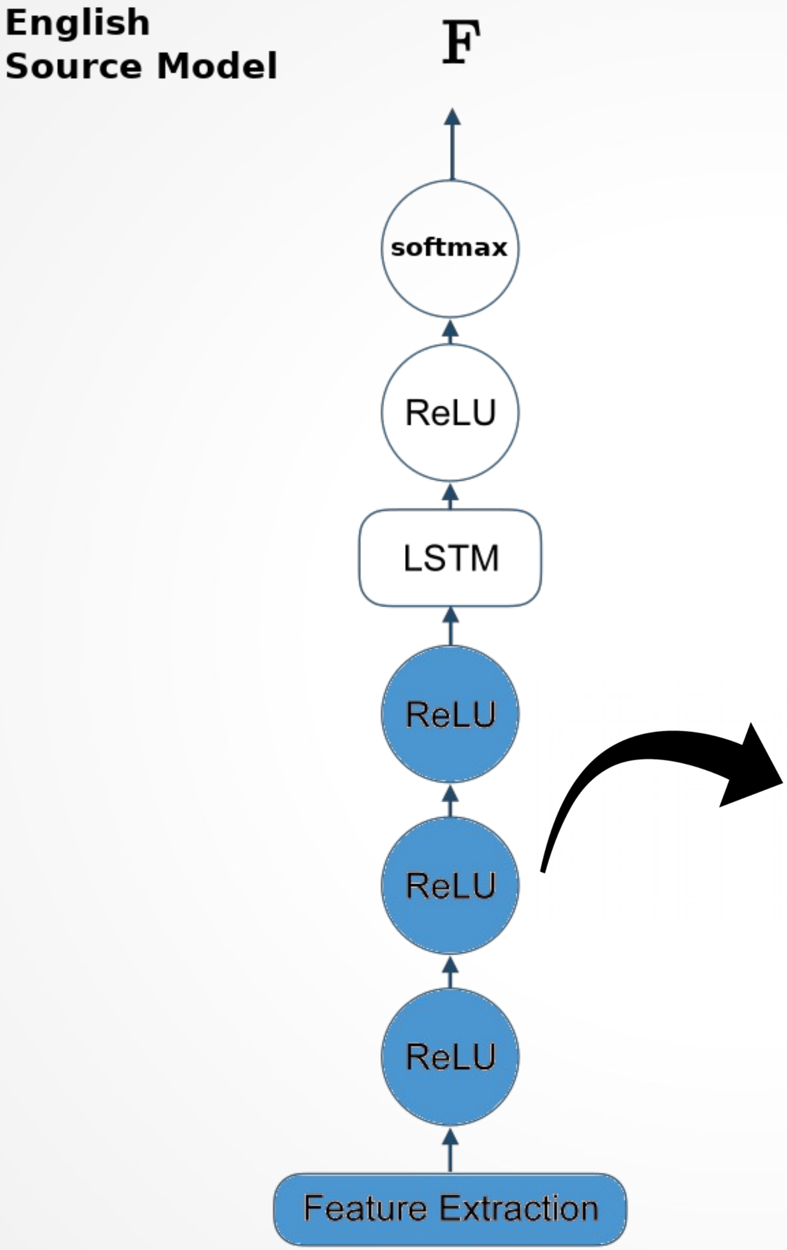

C
A
T
softmax
softmax
softmax
ReLU
ReLU
ReLU
LSTM
LSTM
LSTM
ReLU
ReLU
ReLU
ReLU
ReLU
ReLU
ReLU
ReLU
ReLU
Feature Extraction
Feature Extraction
Feature Extraction

Transfer Experiments

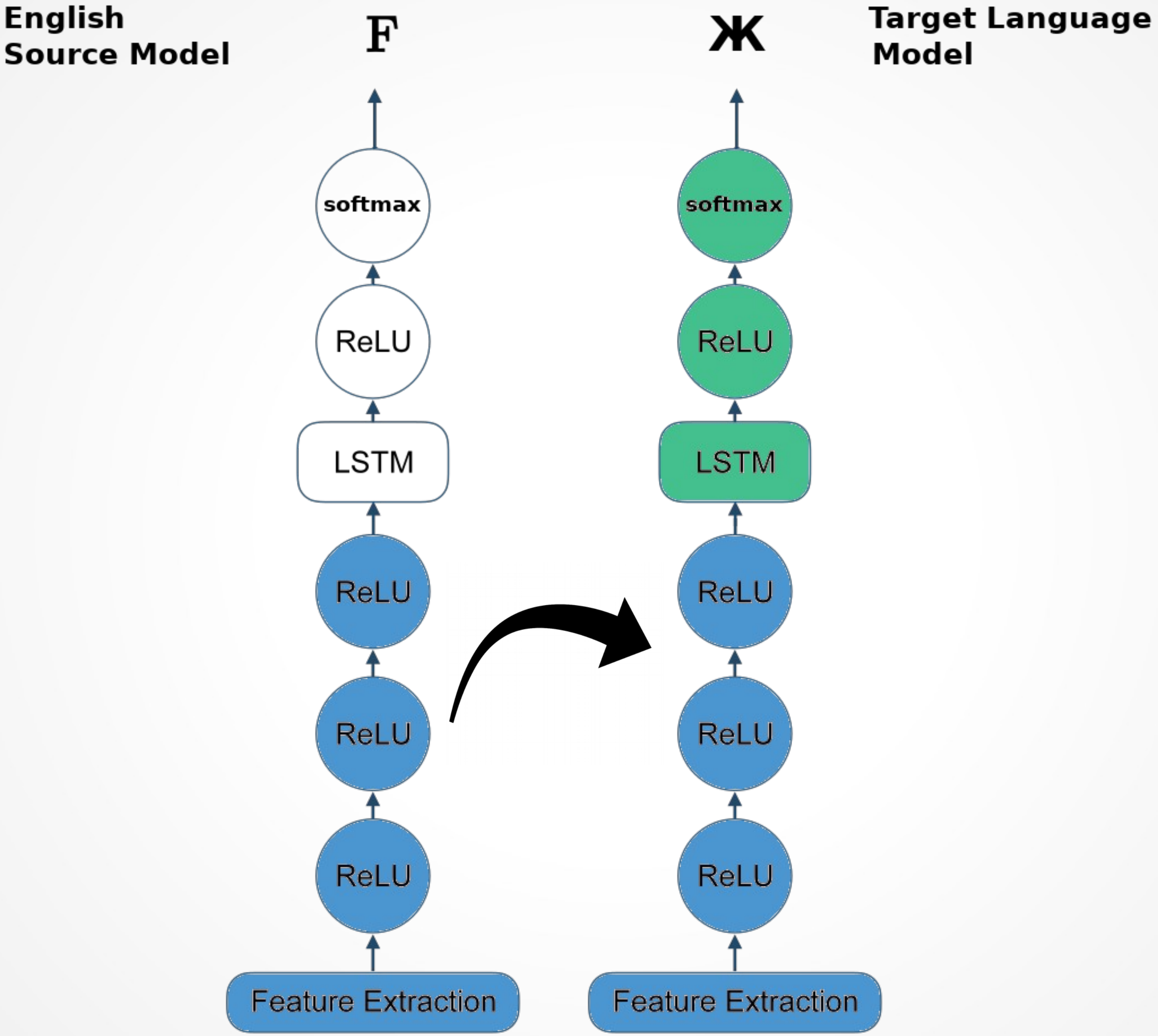
Transfer Experiments



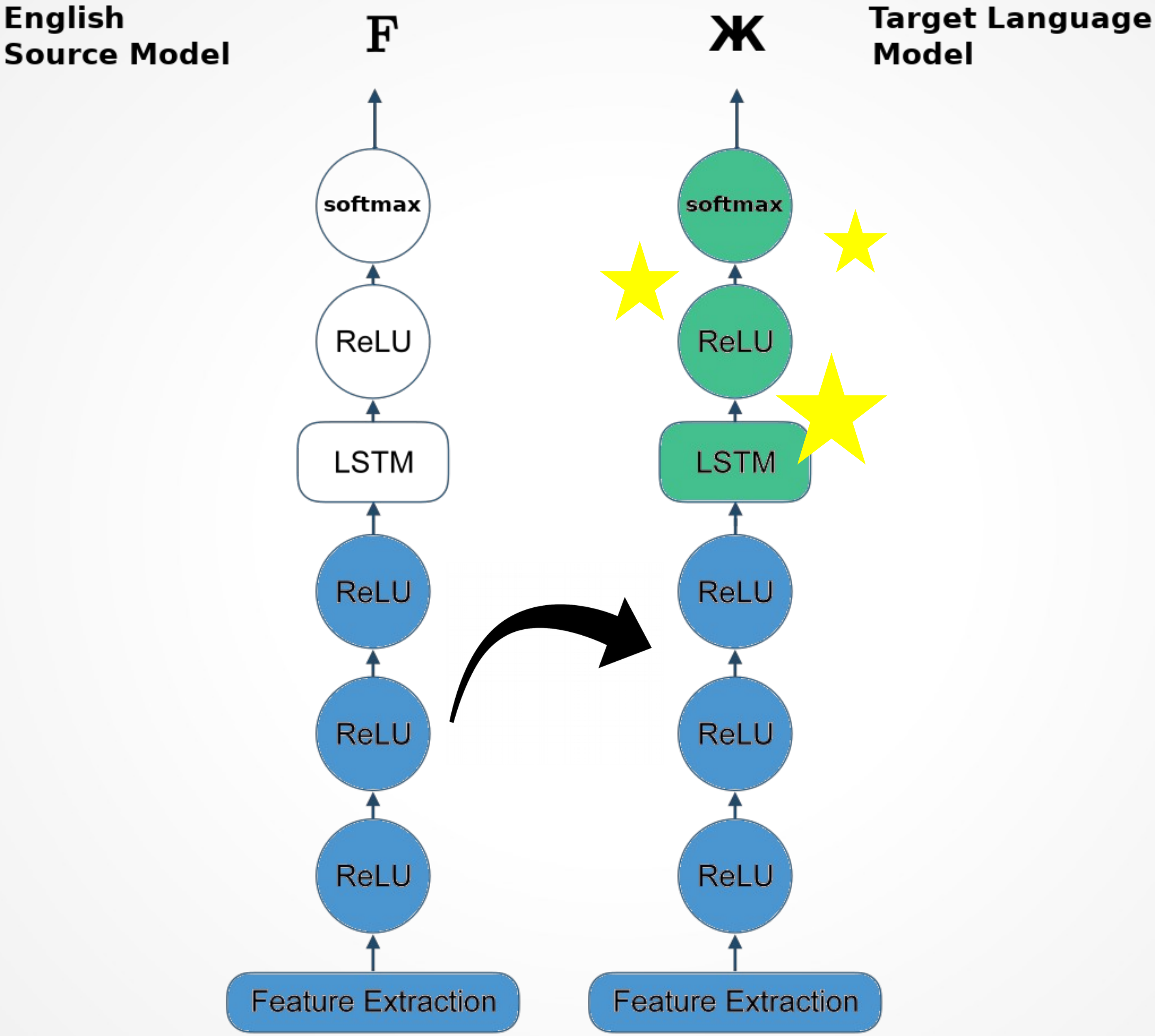
Transfer Experiments



CTC Transfer Experiments



CTC Transfer Experiments



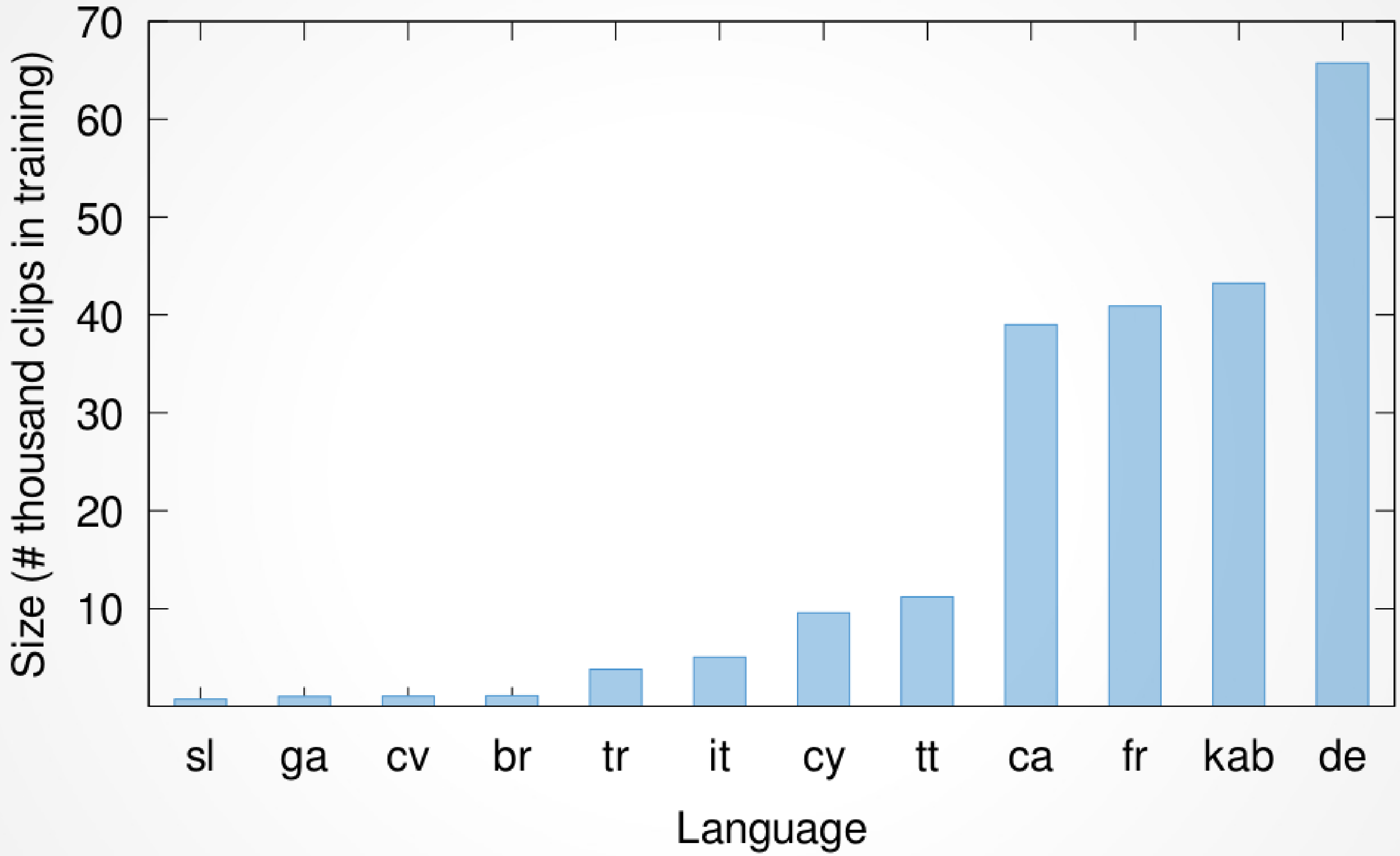
Experimental Design

- 5 depths for slicing source model
- 2 update scenarios (frozen vs. fine-tuned)
- 12 target languages
- 120 experiments, in total

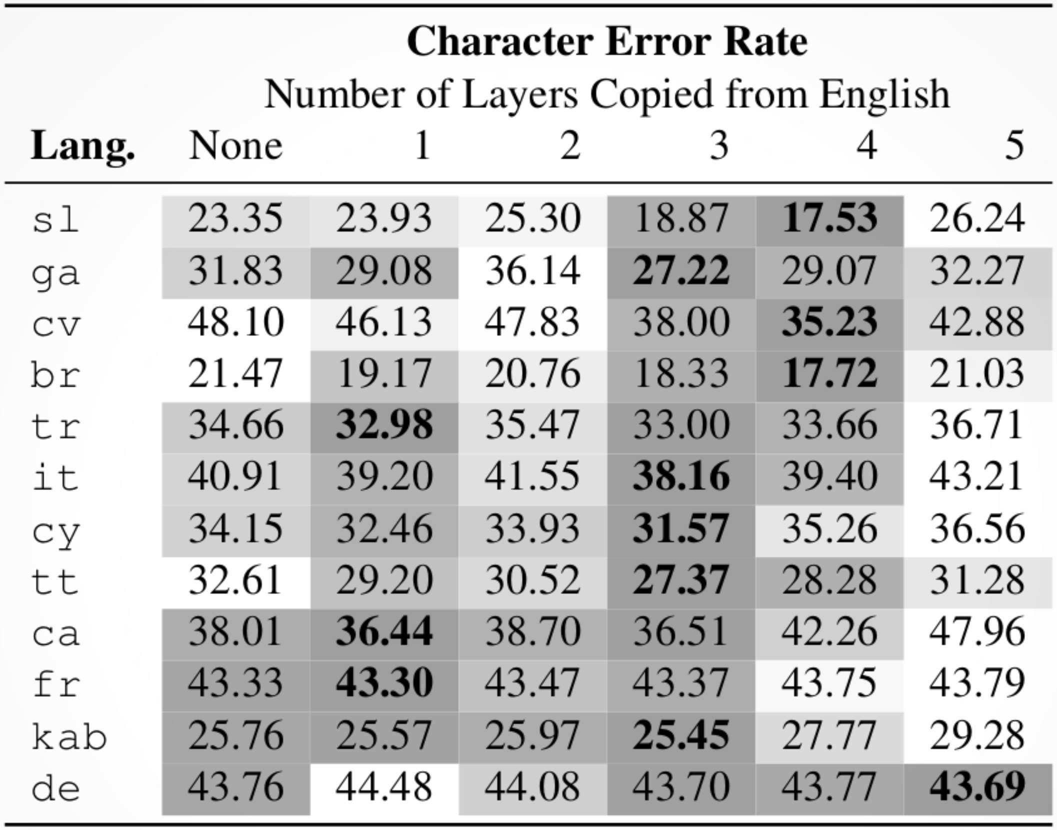
Hyperparameters

- Single GPU training
- 24 train batch, 48 dev batch
- 20% dropout rate
- 0.0001 learning rate with ADAM
- Early stopping based on last 5 steps

Data (Common Voice)



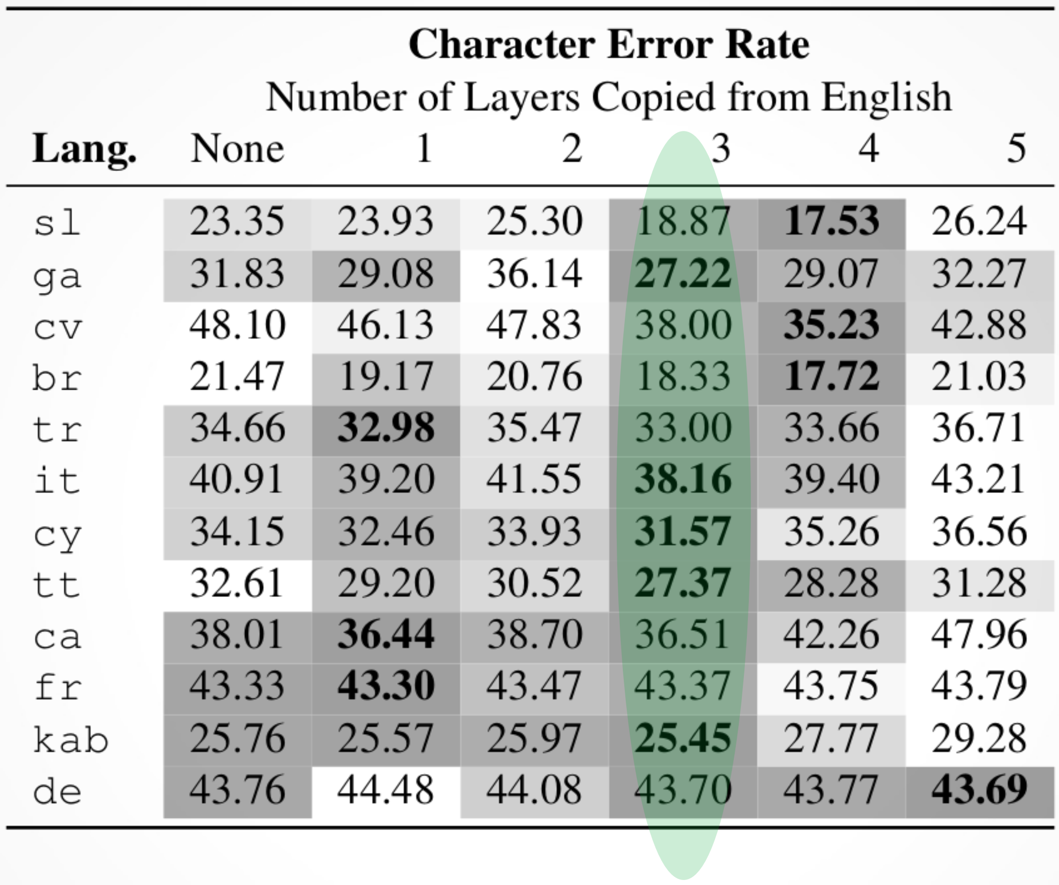
Frozen Transfer Results



	Character Error Rate					
	Number of Layers Copied from English					
Lang.	None	1	2	3	4	5
sl	23.35	23.93	25.30	18.87	**17.53**	26.24
ga	31.83	29.08	36.14	**27.22**	29.07	32.27
cv	48.10	46.13	47.83	38.00	**35.23**	42.88
br	21.47	19.17	20.76	18.33	**17.72**	21.03
tr	34.66	**32.98**	35.47	33.00	33.66	36.71
it	40.91	39.20	41.55	**38.16**	39.40	43.21
cy	34.15	32.46	33.93	**31.57**	35.26	36.56
tt	32.61	29.20	30.52	**27.37**	28.28	31.28
ca	38.01	**36.44**	38.70	36.51	42.26	47.96
fr	43.33	**43.30**	43.47	43.37	43.75	43.79
kab	25.76	25.57	25.97	**25.45**	27.77	29.28
de	43.76	44.48	44.08	43.70	43.77	**43.69**

Table 2. Frozen Transfer Learning Character-error rates (CER)

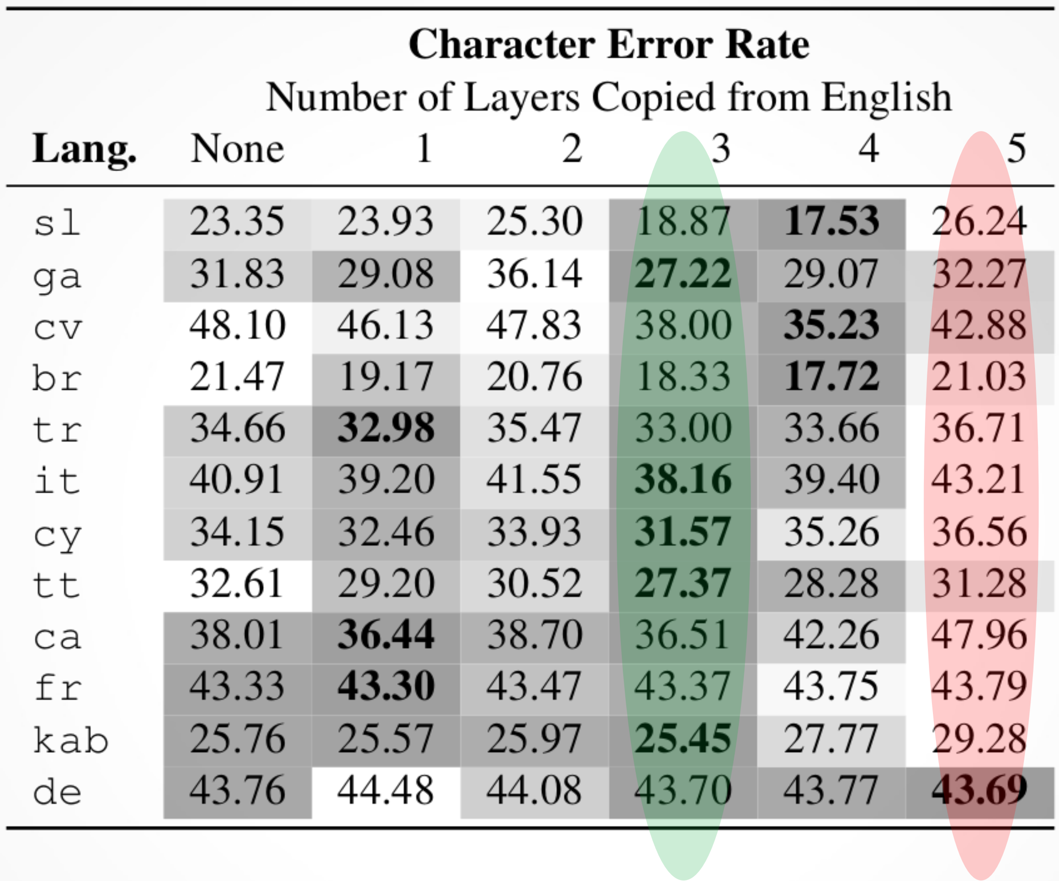
Frozen Transfer Results



	Character Error Rate					
	Number of Layers Copied from English					
Lang.	None	1	2	3	4	5
sl	23.35	23.93	25.30	18.87	**17.53**	26.24
ga	31.83	29.08	36.14	**27.22**	29.07	32.27
cv	48.10	46.13	47.83	38.00	**35.23**	42.88
br	21.47	19.17	20.76	18.33	**17.72**	21.03
tr	34.66	**32.98**	35.47	33.00	33.66	36.71
it	40.91	39.20	41.55	**38.16**	39.40	43.21
cy	34.15	32.46	33.93	**31.57**	35.26	36.56
tt	32.61	29.20	30.52	**27.37**	28.28	31.28
ca	38.01	**36.44**	38.70	36.51	42.26	47.96
fr	43.33	**43.30**	43.47	43.37	43.75	43.79
kab	25.76	25.57	25.97	**25.45**	27.77	29.28
de	43.76	44.48	44.08	43.70	43.77	**43.69**

Table 2. Frozen Transfer Learning Character-error rates (CER)

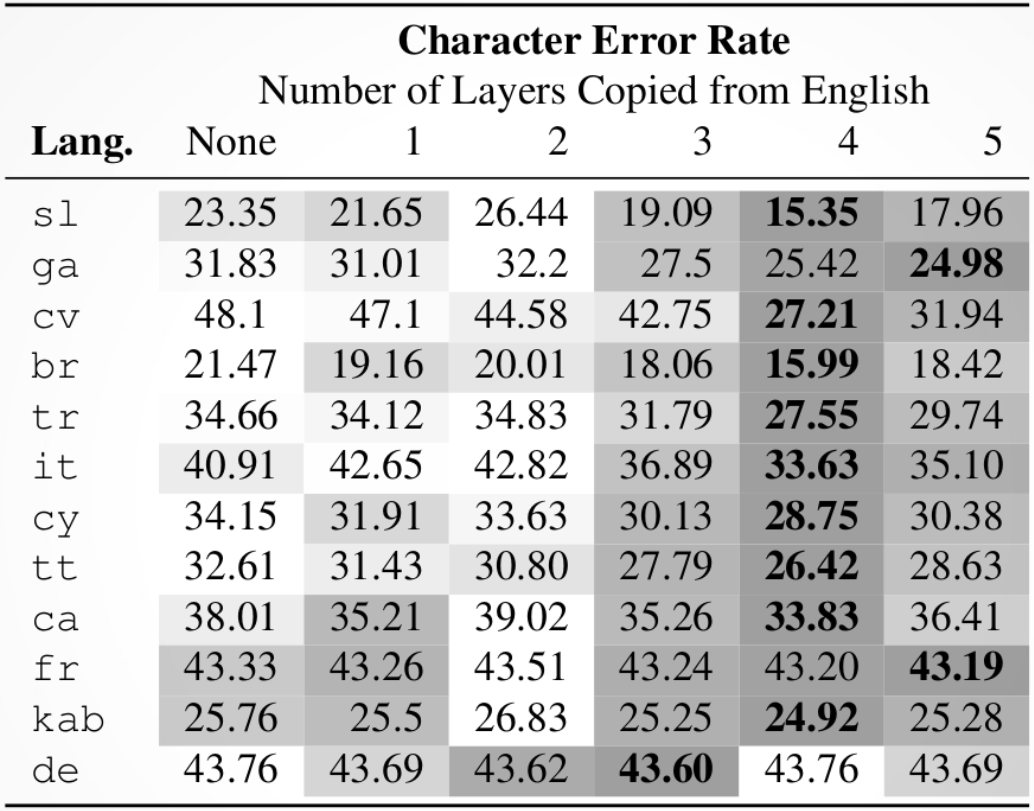
Frozen Transfer Results



	Character Error Rate					
	Number of Layers Copied from English					
Lang.	None	1	2	3	4	5
sl	23.35	23.93	25.30	18.87	**17.53**	26.24
ga	31.83	29.08	36.14	**27.22**	29.07	32.27
cv	48.10	46.13	47.83	38.00	**35.23**	42.88
br	21.47	19.17	20.76	18.33	**17.72**	21.03
tr	34.66	**32.98**	35.47	33.00	33.66	36.71
it	40.91	39.20	41.55	**38.16**	39.40	43.21
cy	34.15	32.46	33.93	**31.57**	35.26	36.56
tt	32.61	29.20	30.52	**27.37**	28.28	31.28
ca	38.01	**36.44**	38.70	36.51	42.26	47.96
fr	43.33	**43.30**	43.47	43.37	43.75	43.79
kab	25.76	25.57	25.97	**25.45**	27.77	29.28
de	43.76	44.48	44.08	43.70	43.77	**43.69**

Table 2. Frozen Transfer Learning Character-error rates (CER)

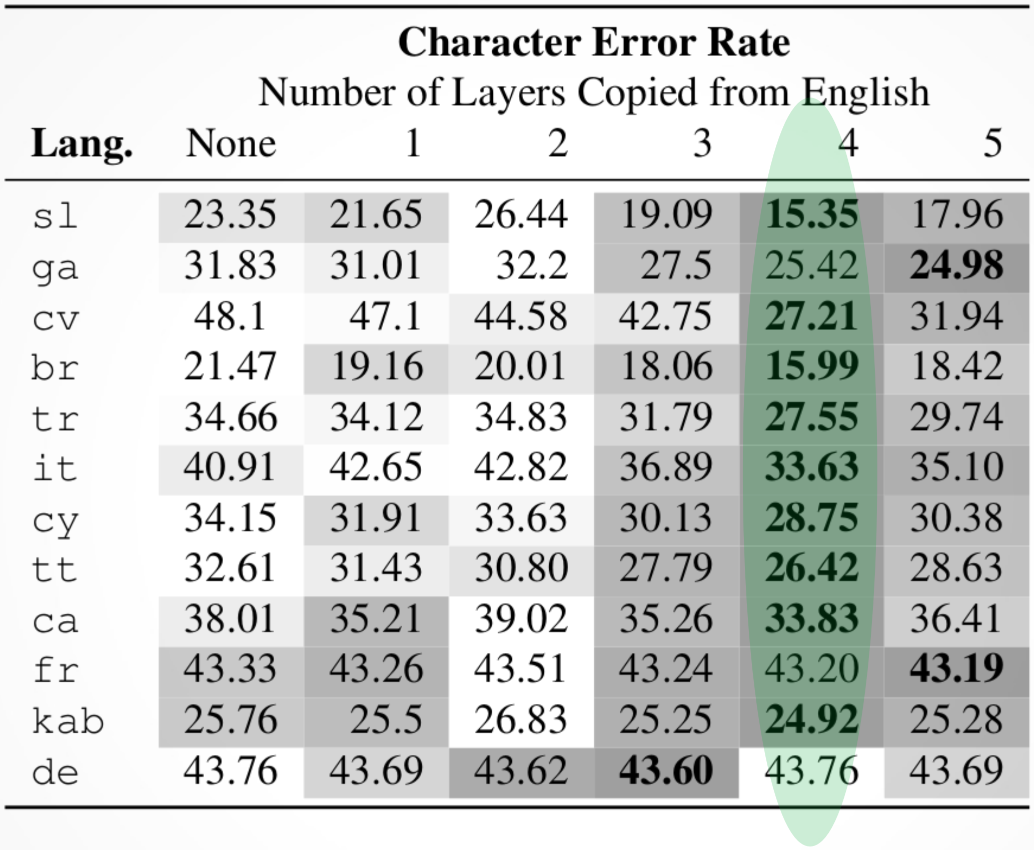
Fine-Tuning Transfer Results



	Character Error Rate					
	Number of Layers Copied from English					
Lang.	None	1	2	3	4	5
sl	23.35	21.65	26.44	19.09	**15.35**	17.96
ga	31.83	31.01	32.2	27.5	25.42	**24.98**
cv	48.1	47.1	44.58	42.75	**27.21**	31.94
br	21.47	19.16	20.01	18.06	**15.99**	18.42
tr	34.66	34.12	34.83	31.79	**27.55**	29.74
it	40.91	42.65	42.82	36.89	**33.63**	35.10
cy	34.15	31.91	33.63	30.13	**28.75**	30.38
tt	32.61	31.43	30.80	27.79	**26.42**	28.63
ca	38.01	35.21	39.02	35.26	**33.83**	36.41
fr	43.33	43.26	43.51	43.24	43.20	**43.19**
kab	25.76	25.5	26.83	25.25	**24.92**	25.28
de	43.76	43.69	43.62	**43.60**	43.76	43.69

Table 3. Fine-Tuned Transfer Learning Character-error rates (CER)

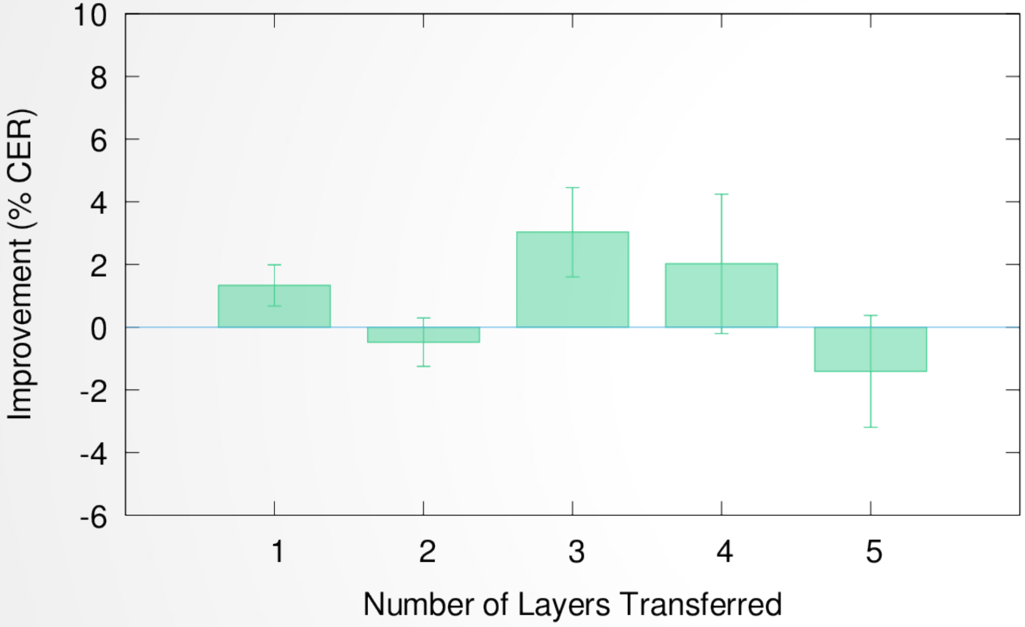
Fine-Tuning Transfer Results

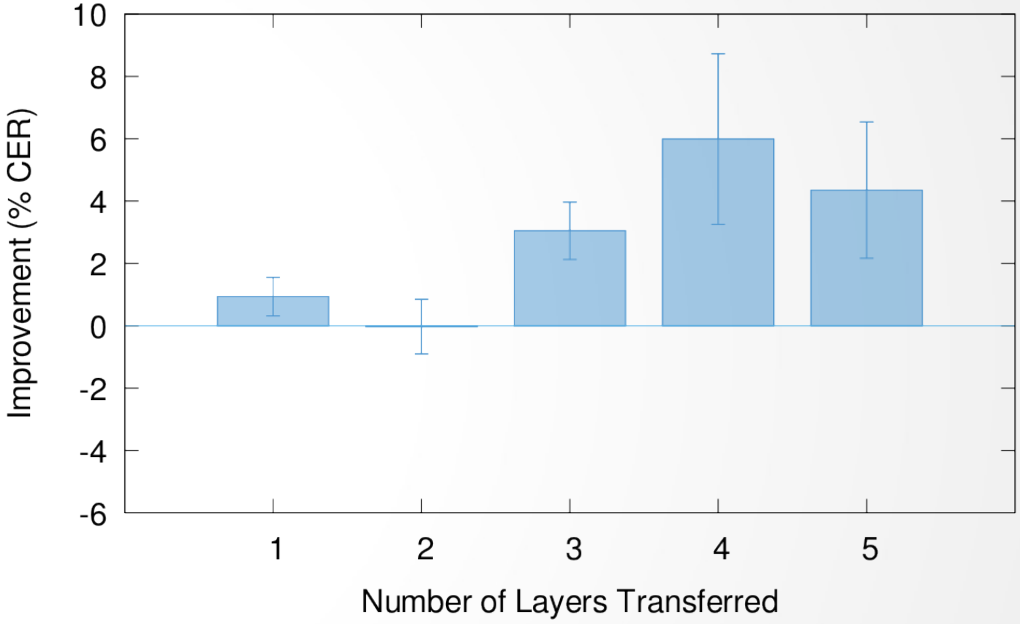


	Character Error Rate					
	Number of Layers Copied from English					
Lang.	None	1	2	3	4	5
`sl`	23.35	21.65	26.44	19.09	**15.35**	17.96
`ga`	31.83	31.01	32.2	27.5	25.42	**24.98**
`cv`	48.1	47.1	44.58	42.75	**27.21**	31.94
`br`	21.47	19.16	20.01	18.06	**15.99**	18.42
`tr`	34.66	34.12	34.83	31.79	**27.55**	29.74
`it`	40.91	42.65	42.82	36.89	**33.63**	35.10
`cy`	34.15	31.91	33.63	30.13	**28.75**	30.38
`tt`	32.61	31.43	30.80	27.79	**26.42**	28.63
`ca`	38.01	35.21	39.02	35.26	**33.83**	36.41
`fr`	43.33	43.26	43.51	43.24	43.20	**43.19**
`kab`	25.76	25.5	26.83	25.25	**24.92**	25.28
`de`	43.76	43.69	43.62	**43.60**	43.76	43.69

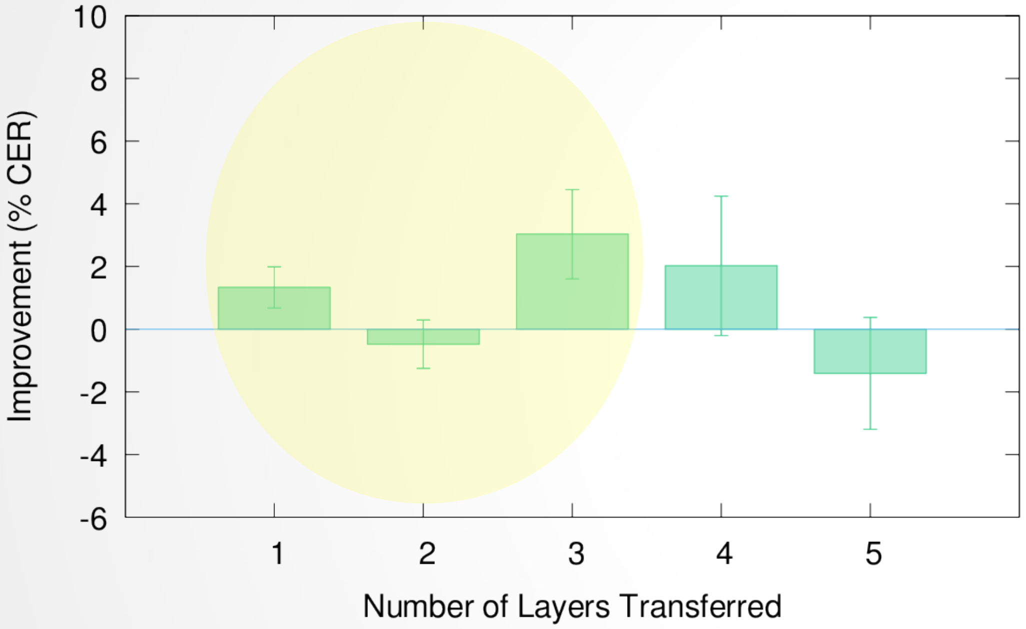
Table 3. Fine-Tuned Transfer Learning Character-error rates (CER)

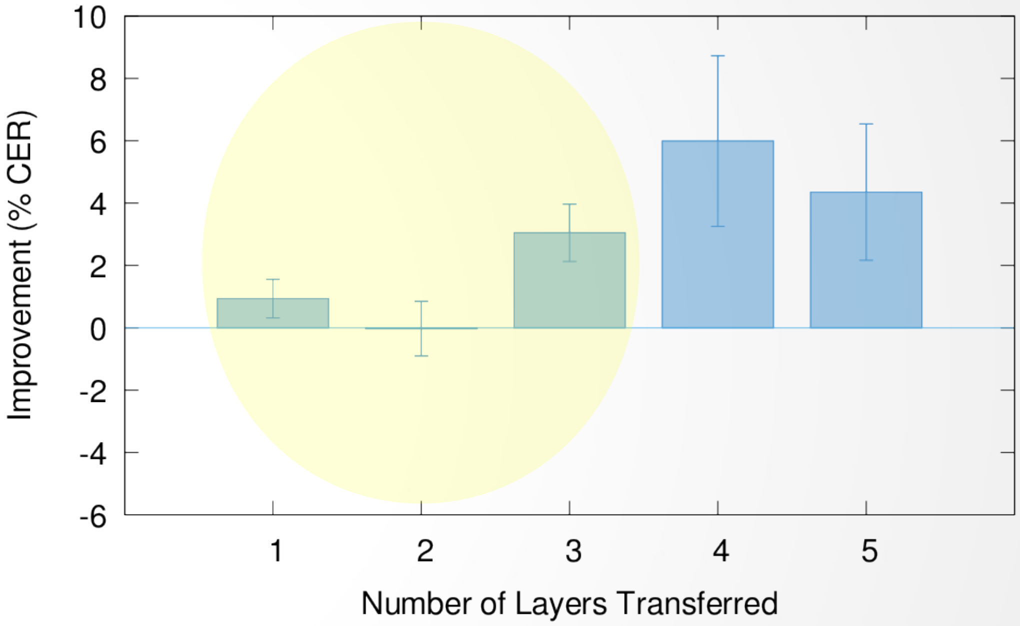
Frozen vs. Fine-Tuned





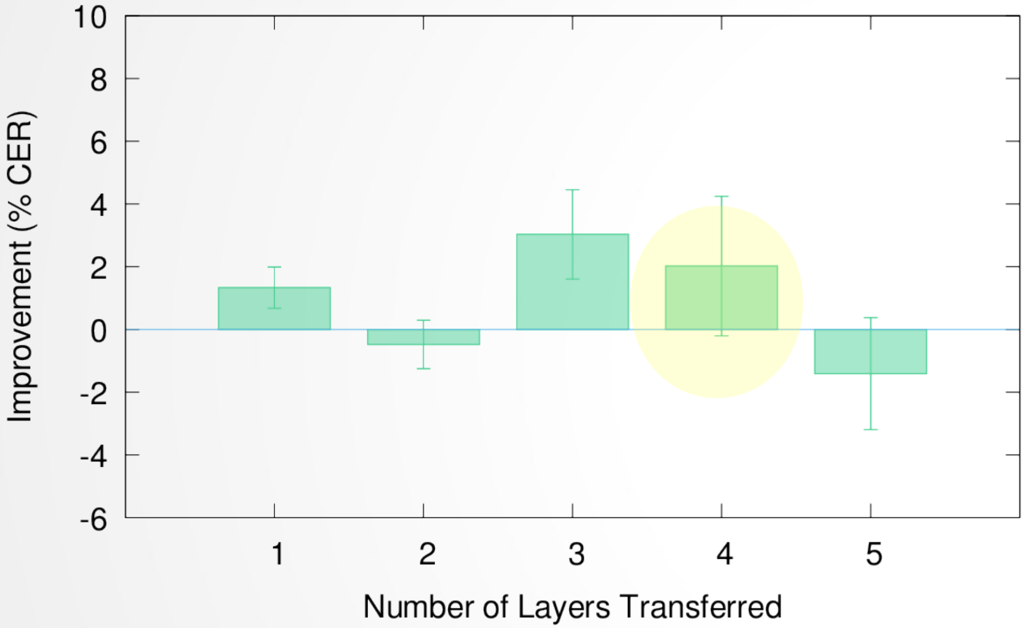
Frozen vs. Fine-Tuned

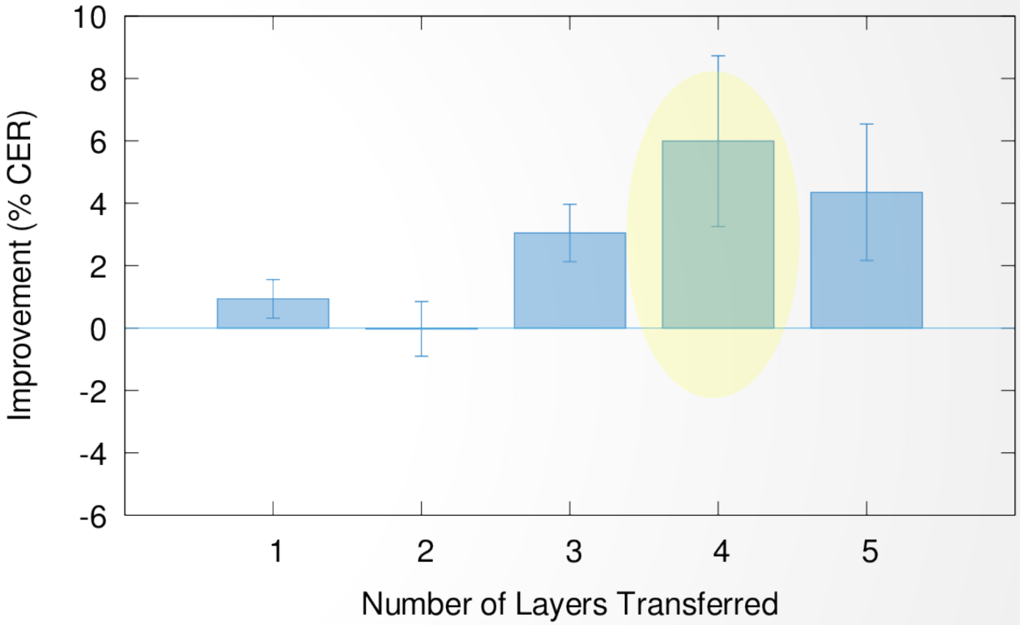




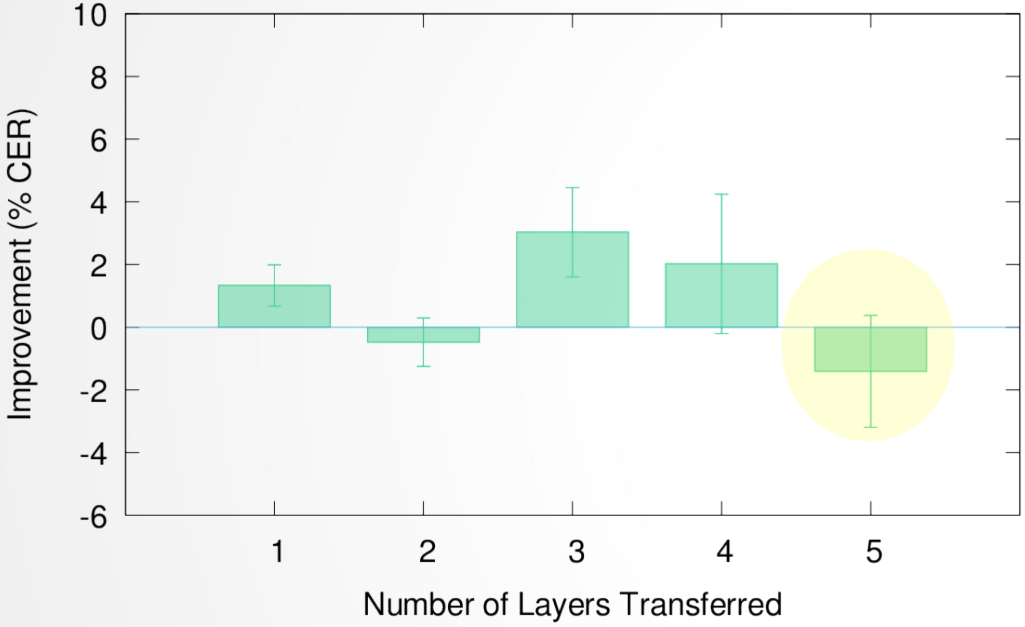
Frozen vs. Fine-Tuned

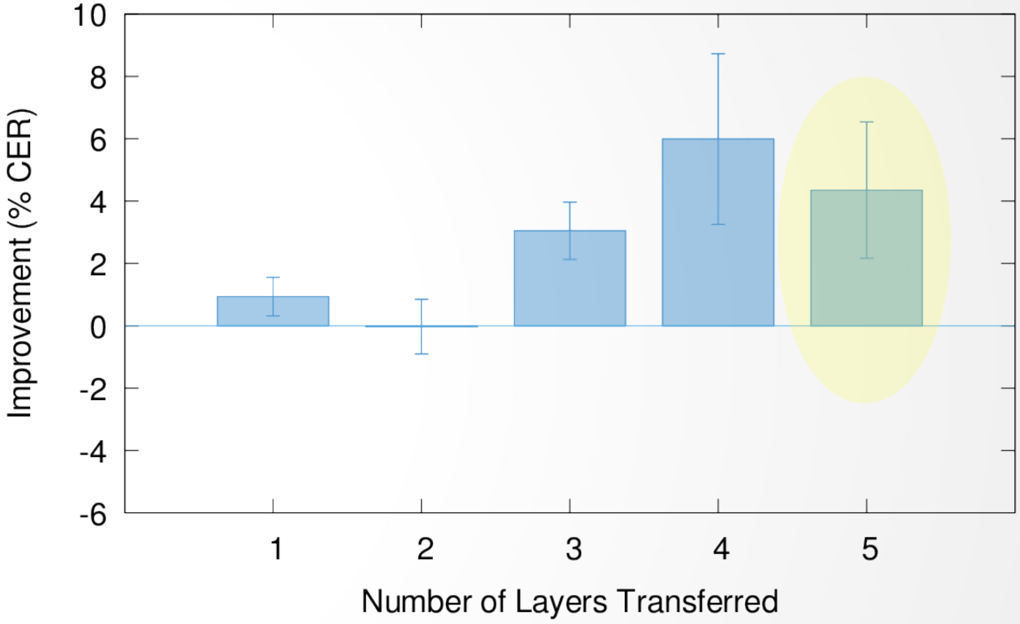
LSTM!





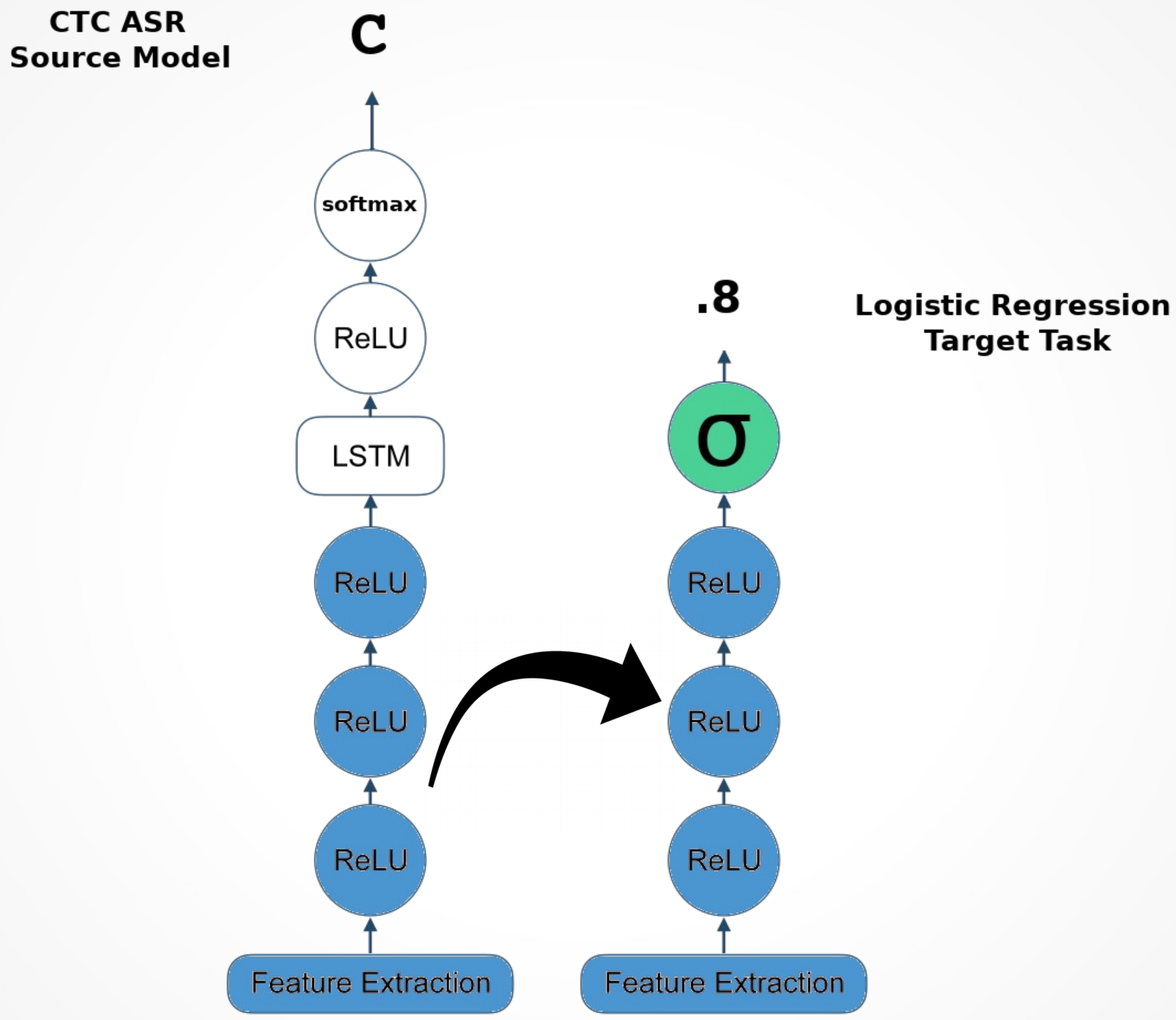
Frozen vs. Fine-Tuned



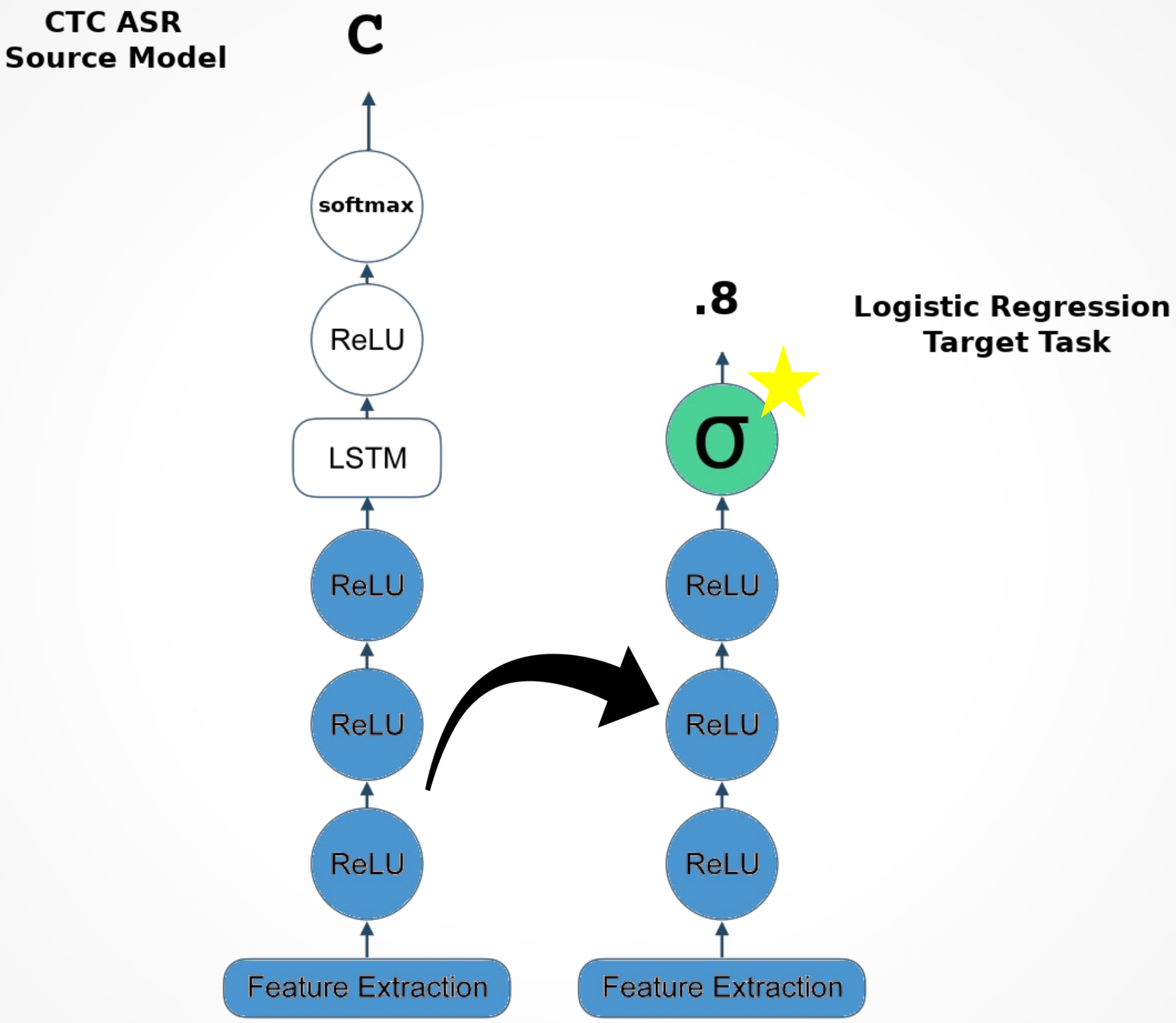


Interpretability Experiments

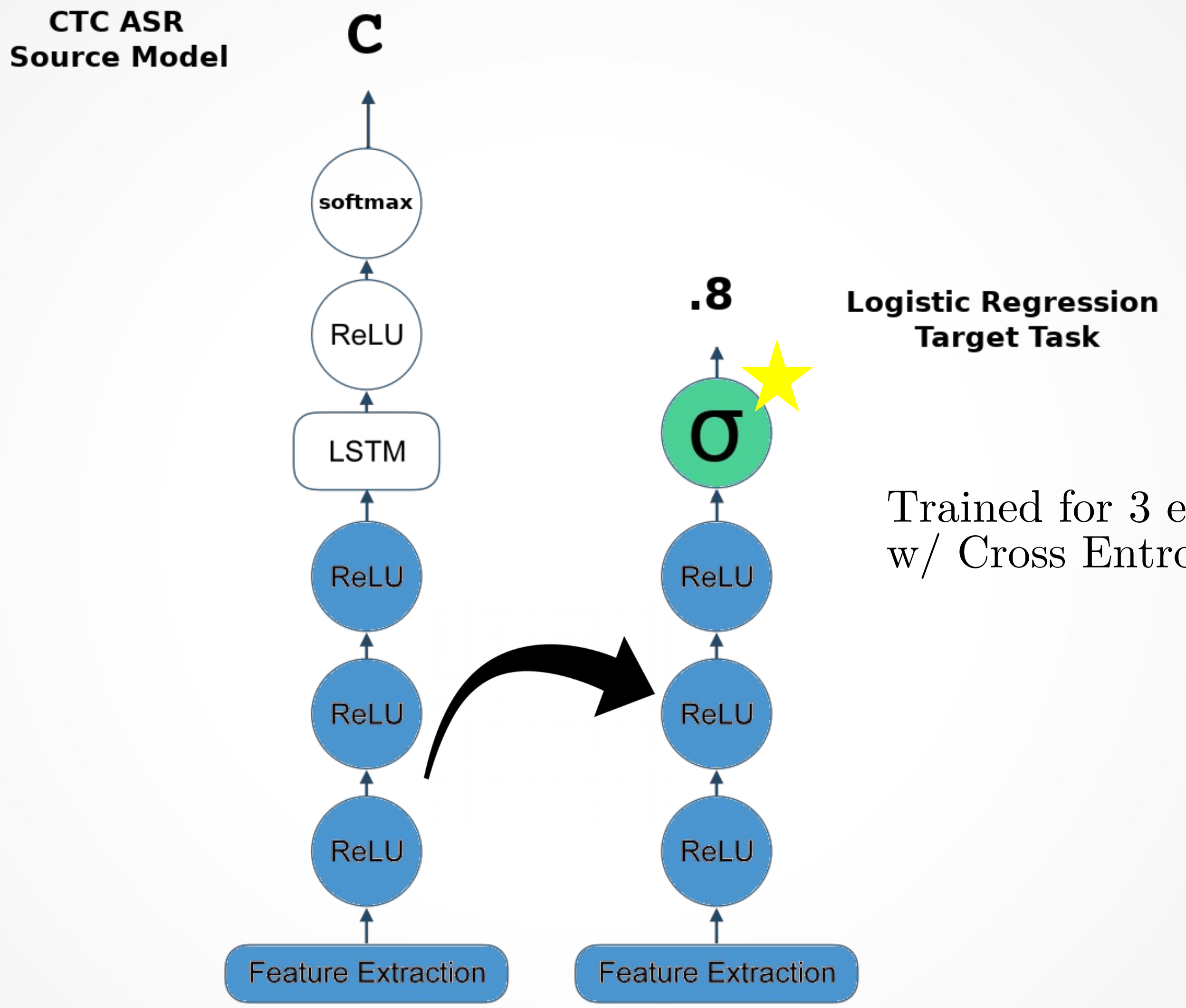
Regression on Embeddings



Regression on Embeddings



Regression on Embeddings



Trained for 3 epochs
w/ Cross Entropy Loss

Regression Results

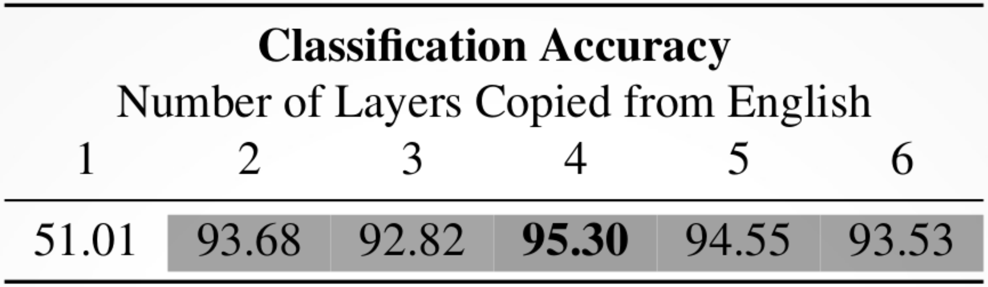
Speech vs. Noise

Regression Results

Speech vs. Noise

- Copied layers, added final FC layer with single output and logistic activation
- 13 languages vs. UrbanSound8k
- 5,005 train clips, 442 test clips per class

Regression Results

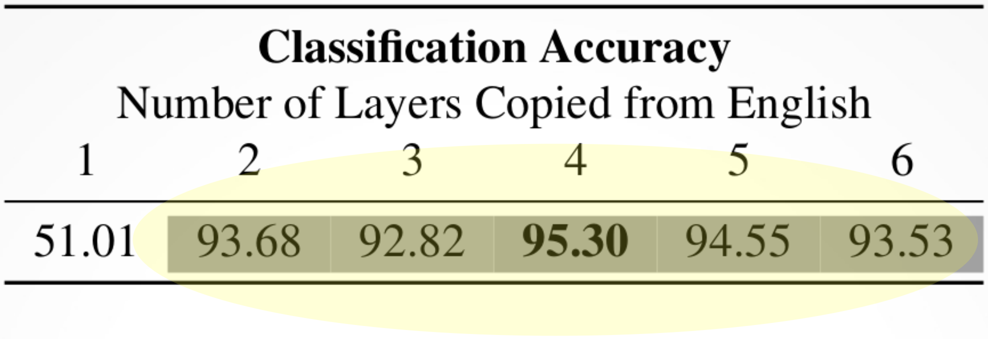


Classification Accuracy					
Number of Layers Copied from English					
1	2	3	4	5	6
51.01	93.68	92.82	**95.30**	94.55	93.53

Table 4. Speech vs. Non-Speech Audio Classification Accuracy

- Copied layers, added final FC layer with single output and logistic activation
- 13 languages vs. UrbanSound8k
- 5,005 train clips, 442 test clips per class

Regression Results



Classification Accuracy					
Number of Layers Copied from English					
1	2	3	4	5	6
51.01	93.68	92.82	**95.30**	94.55	93.53

Table 4. Speech vs. Non-Speech Audio Classification Accuracy

- Copied layers, added final FC layer with single output and logistic activation
- 13 languages vs. UrbanSound8k
- 5,005 train clips, 442 test clips per class

Regression Results

English vs. German

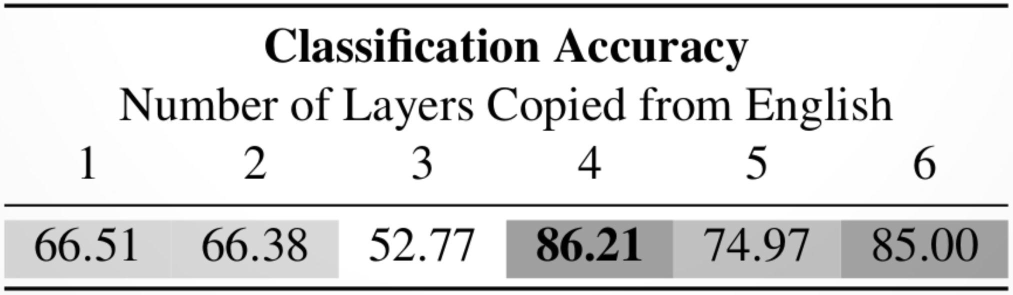
Regression Results

English vs. German

- Copied layers, added final FC layer with single output and logistic activation
- English vs. German
- 5,000 train clips, 500 test clips per class

Regression Results

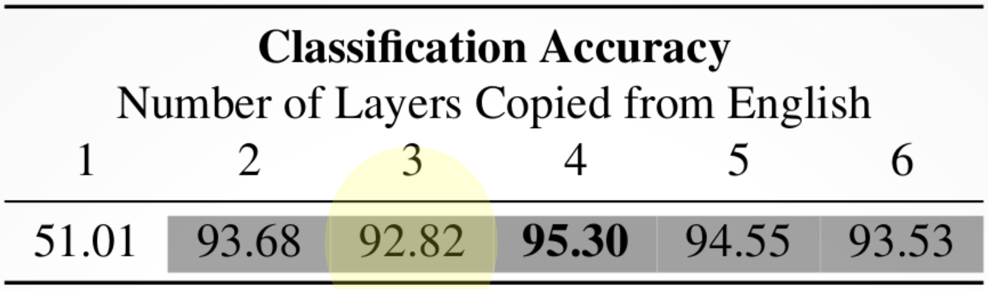
English vs. German



Classification Accuracy					
Number of Layers Copied from English					
1	2	3	4	5	6
66.51	66.38	52.77	**86.21**	74.97	85.00

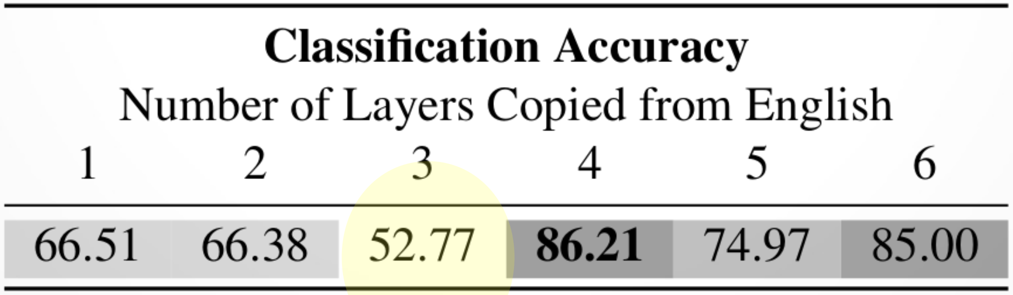
Table 5. English vs. German Audio Classification Accuracy (%)

Regression Results



Classification Accuracy					
Number of Layers Copied from English					
1	2	3	4	5	6
51.01	93.68	92.82	**95.30**	94.55	93.53

Table 4. Speech vs. Non-Speech Audio Classification Accuracy



Classification Accuracy					
Number of Layers Copied from English					
1	2	3	4	5	6
66.51	66.38	52.77	**86.21**	74.97	85.00

Table 5. English vs. German Audio Classification Accuracy (%)

Summary: End-to-end Transfer

Multilingual Transfer

- Fine-tuning always helps
- LSTM transfer is best, but only with fine-tuning

Interpretability Studies

- Before the recursive Layer, the model has **Language-specific** and **language-agnostic** representations

Summary: A Dissertation

Multi-Task Studies

- Abstract linguistic representations **are** helpful
- Engineered Tasks can discover useful bias in the phonetic decision tree
- Relative Task weighting is crucial to success

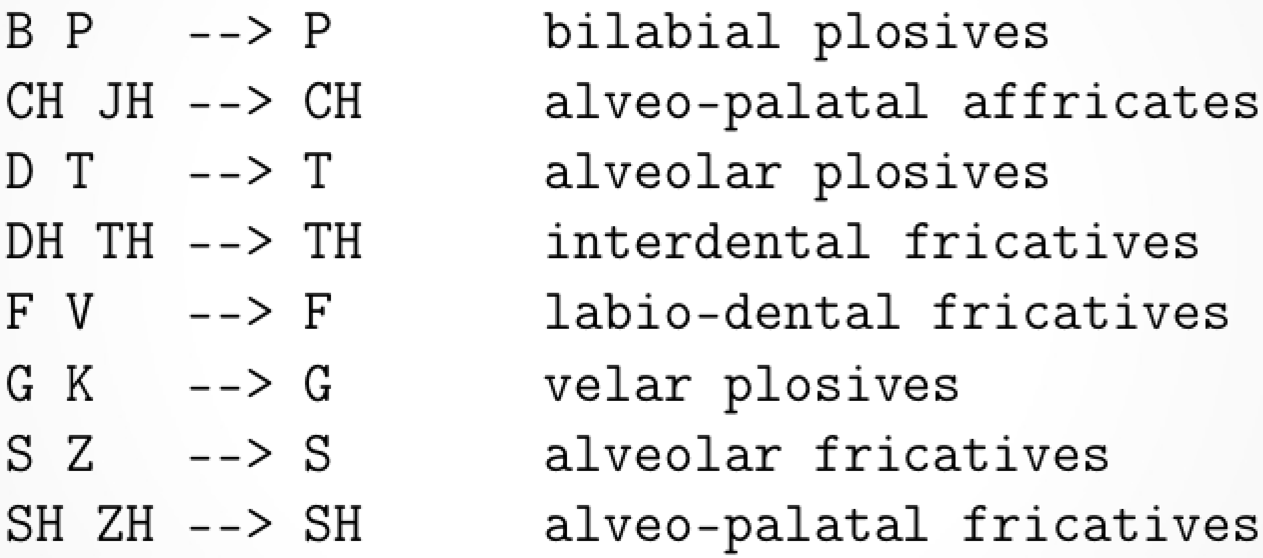
Copy-Paste Transfer Studies

- Transfer with fine-tuning always helps
- The source model has learned Language-general representations before recurrent knowledge is possible

APPENDIX A: Multi-Task

Linguistic Knowledge

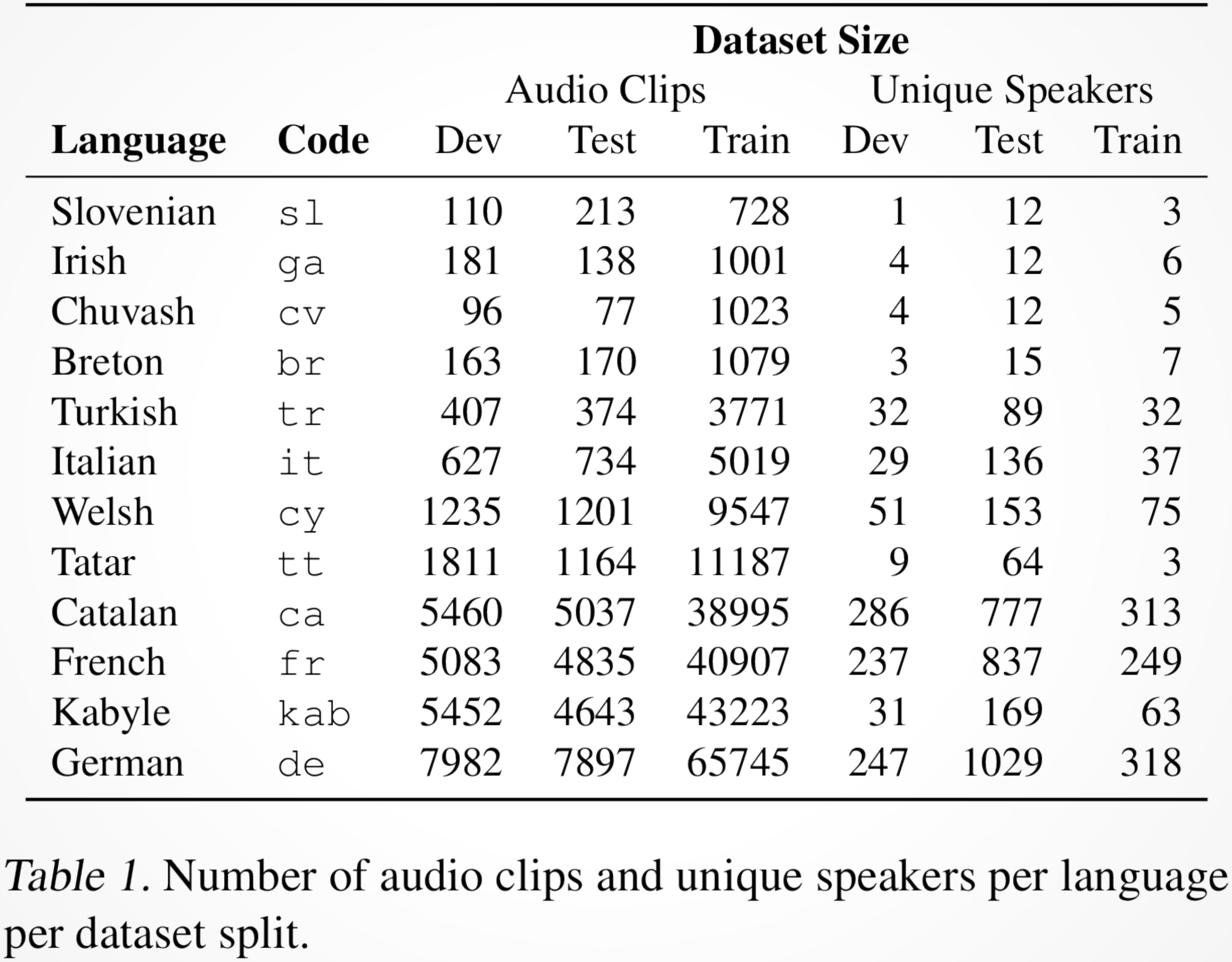
Example: Collapsing on Voice



```
B P   --> P       bilabial plosives
CH JH --> CH      alveo-palatal affricates
D T   --> T       alveolar plosives
DH TH --> TH      interdental fricatives
F V   --> F       labio-dental fricatives
G K   --> G       velar plosives
S Z   --> S       alveolar fricatives
SH ZH --> SH      alveo-palatal fricatives
```

APPENDIX B: DeepSpeech

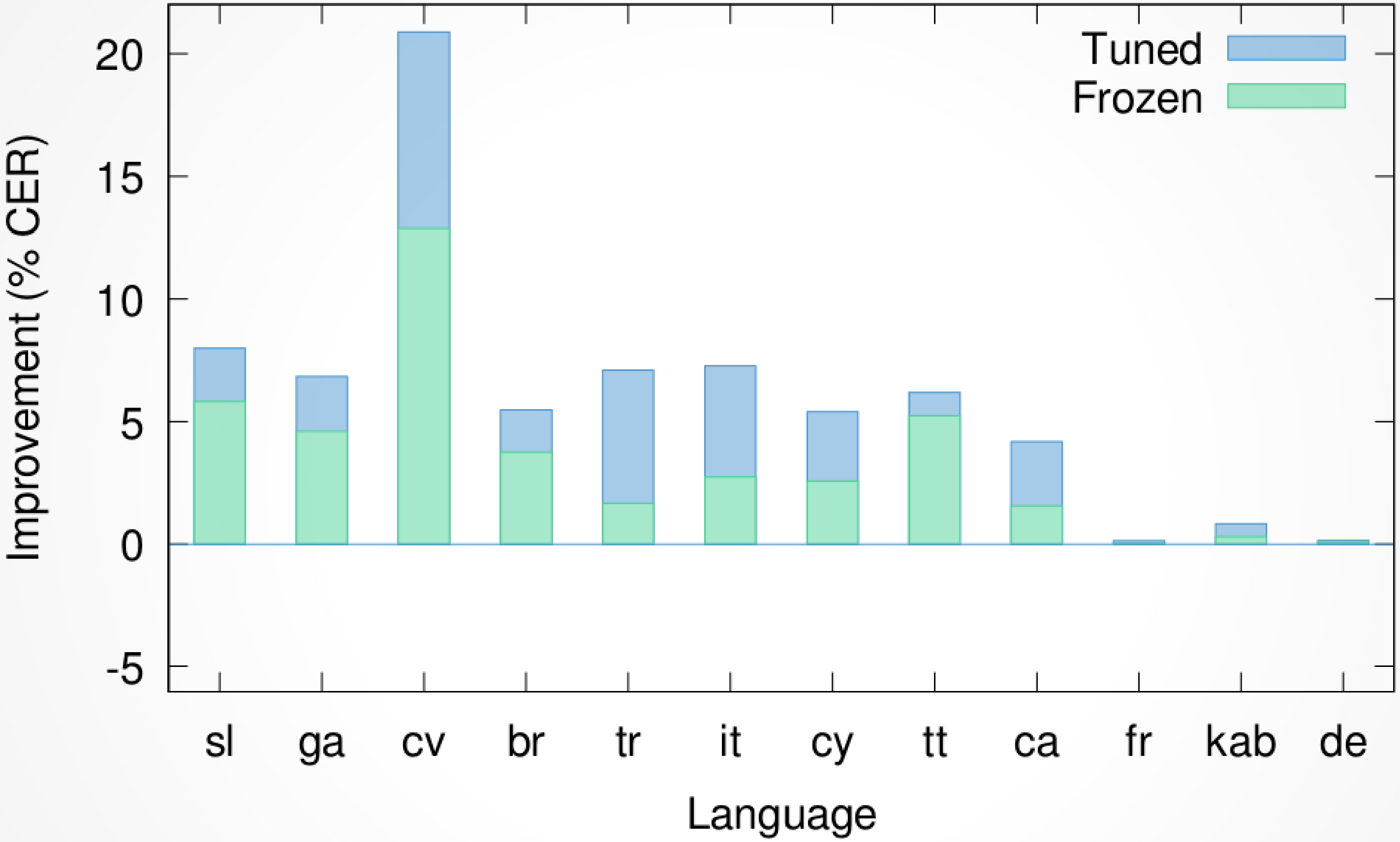
Data Details



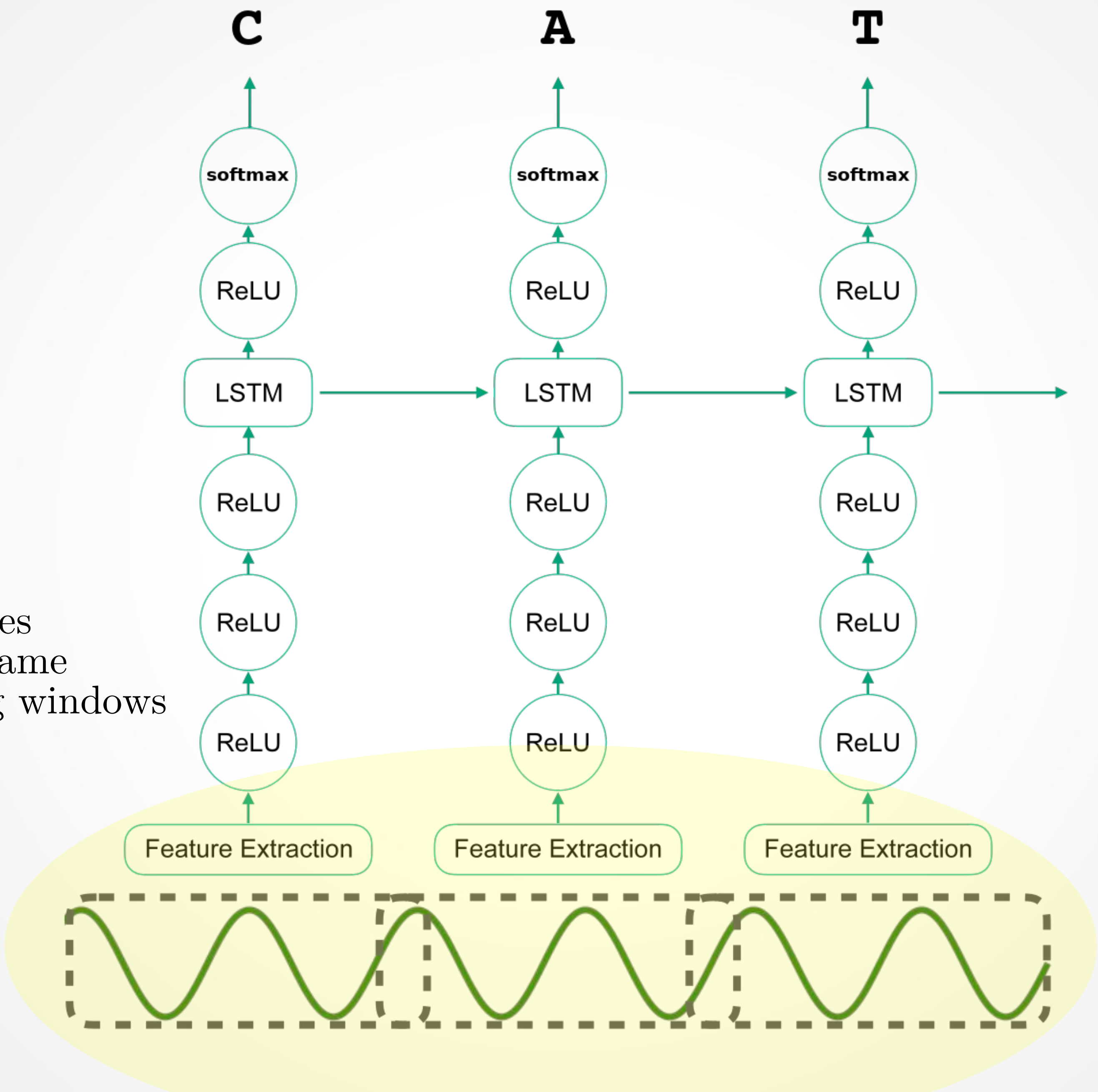
		Dataset Size					
		Audio Clips			Unique Speakers		
Language	**Code**	Dev	Test	Train	Dev	Test	Train
Slovenian	`sl`	110	213	728	1	12	3
Irish	`ga`	181	138	1001	4	12	6
Chuvash	`cv`	96	77	1023	4	12	5
Breton	`br`	163	170	1079	3	15	7
Turkish	`tr`	407	374	3771	32	89	32
Italian	`it`	627	734	5019	29	136	37
Welsh	`cy`	1235	1201	9547	51	153	75
Tatar	`tt`	1811	1164	11187	9	64	3
Catalan	`ca`	5460	5037	38995	286	777	313
French	`fr`	5083	4835	40907	237	837	249
Kabyle	`kab`	5452	4643	43223	31	169	63
German	`de`	7982	7897	65745	247	1029	318

Table 1. Number of audio clips and unique speakers per language per dataset split.

Effect of Data Size



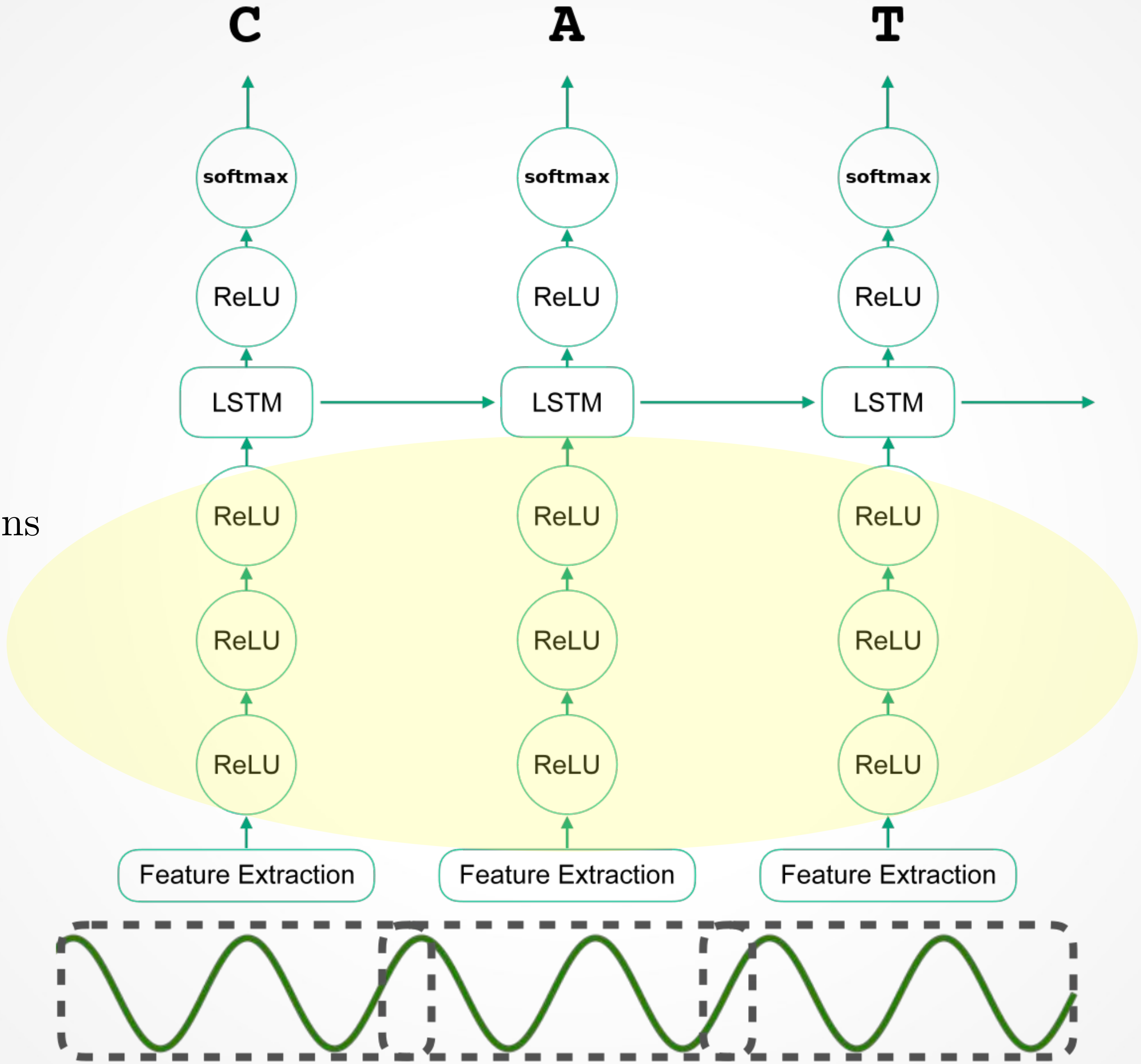
Model Architecture



19 spliced frames
26 MFCCs / frame
32ms Hamming windows
20ms timestep

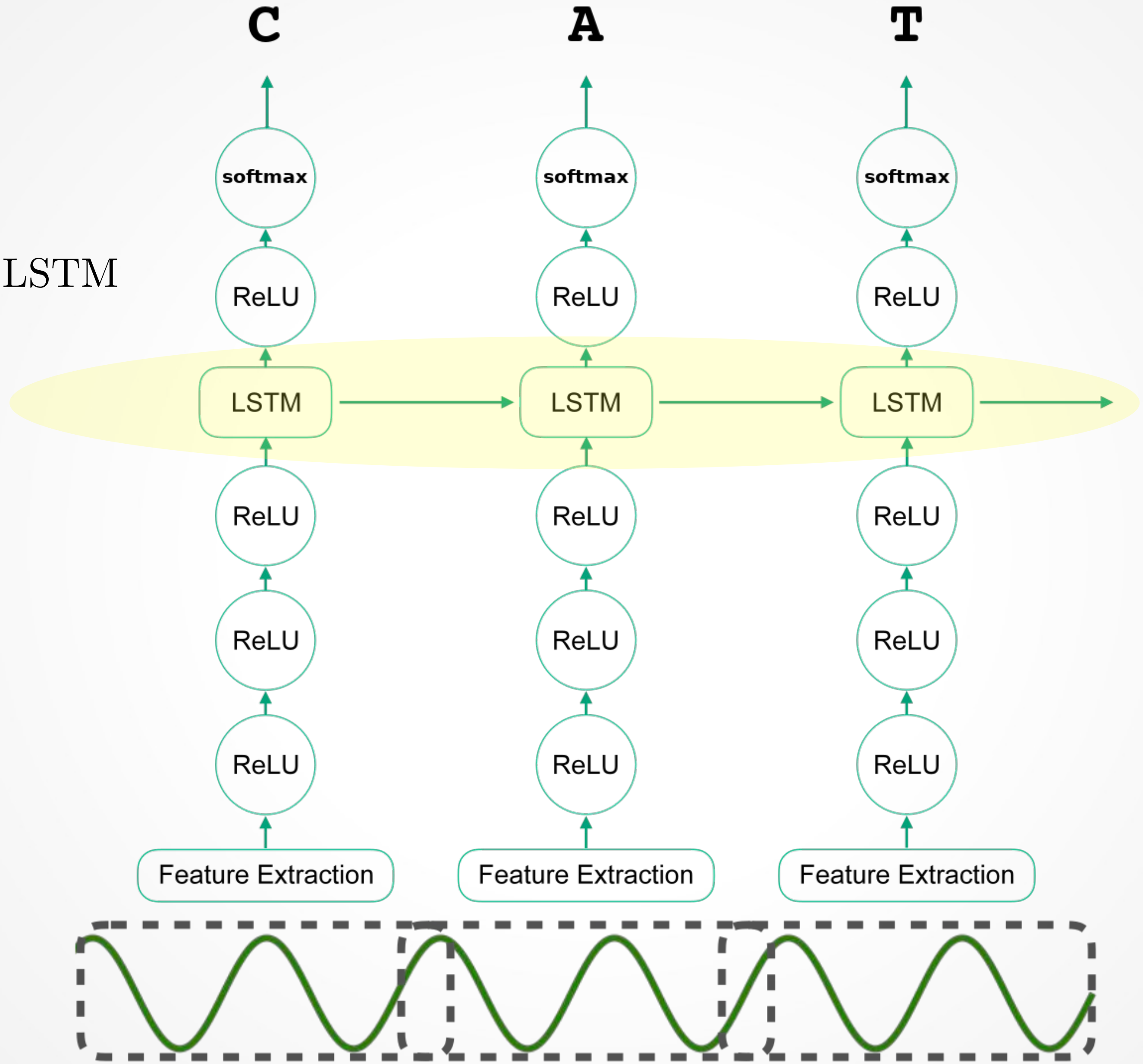
Model Architecture

Fully connected
Feed-Forward
2048 dims
ReLU activiations

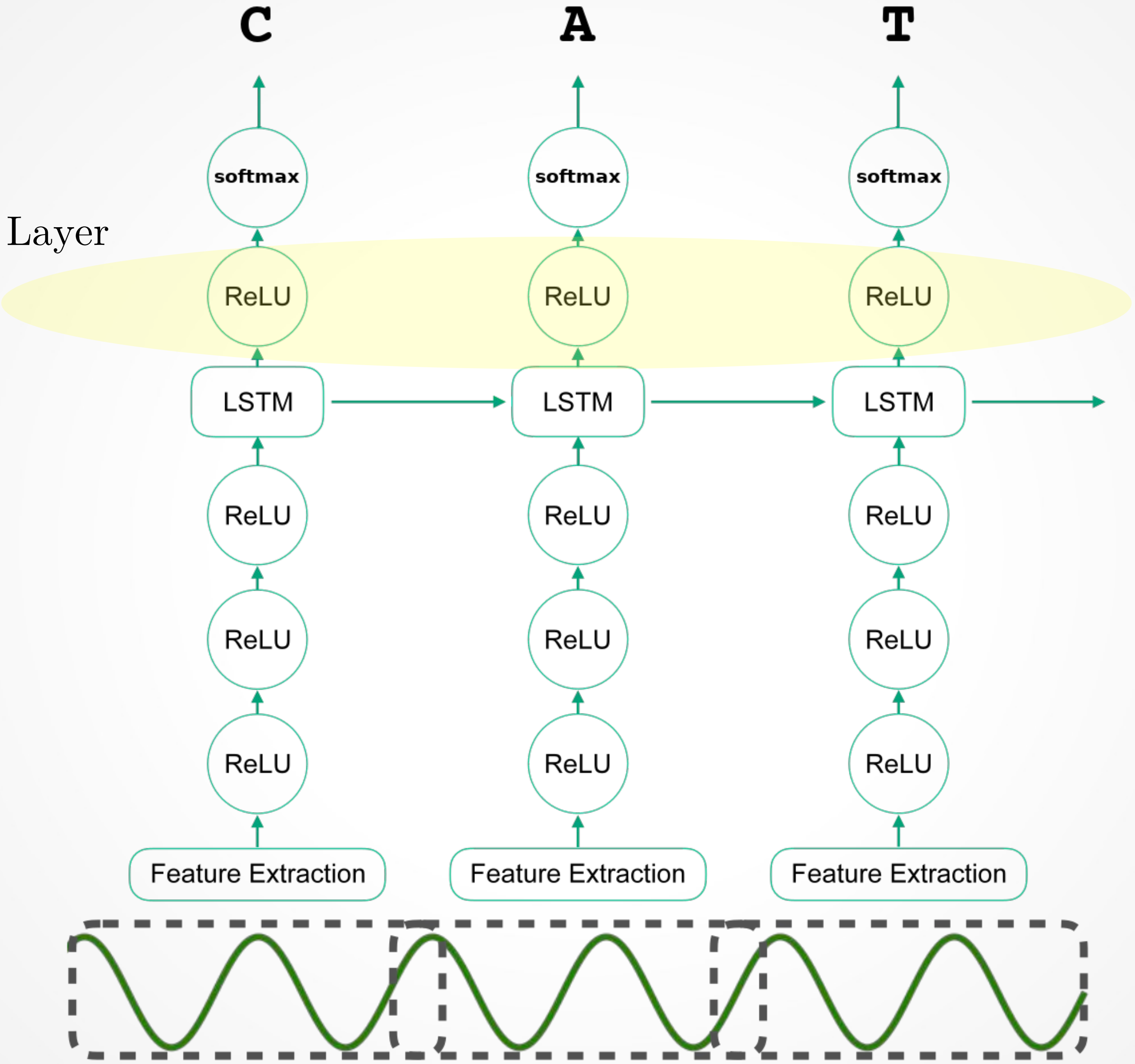


Model Architecture

Unidirectional LSTM
2048 dims



Model Architecture



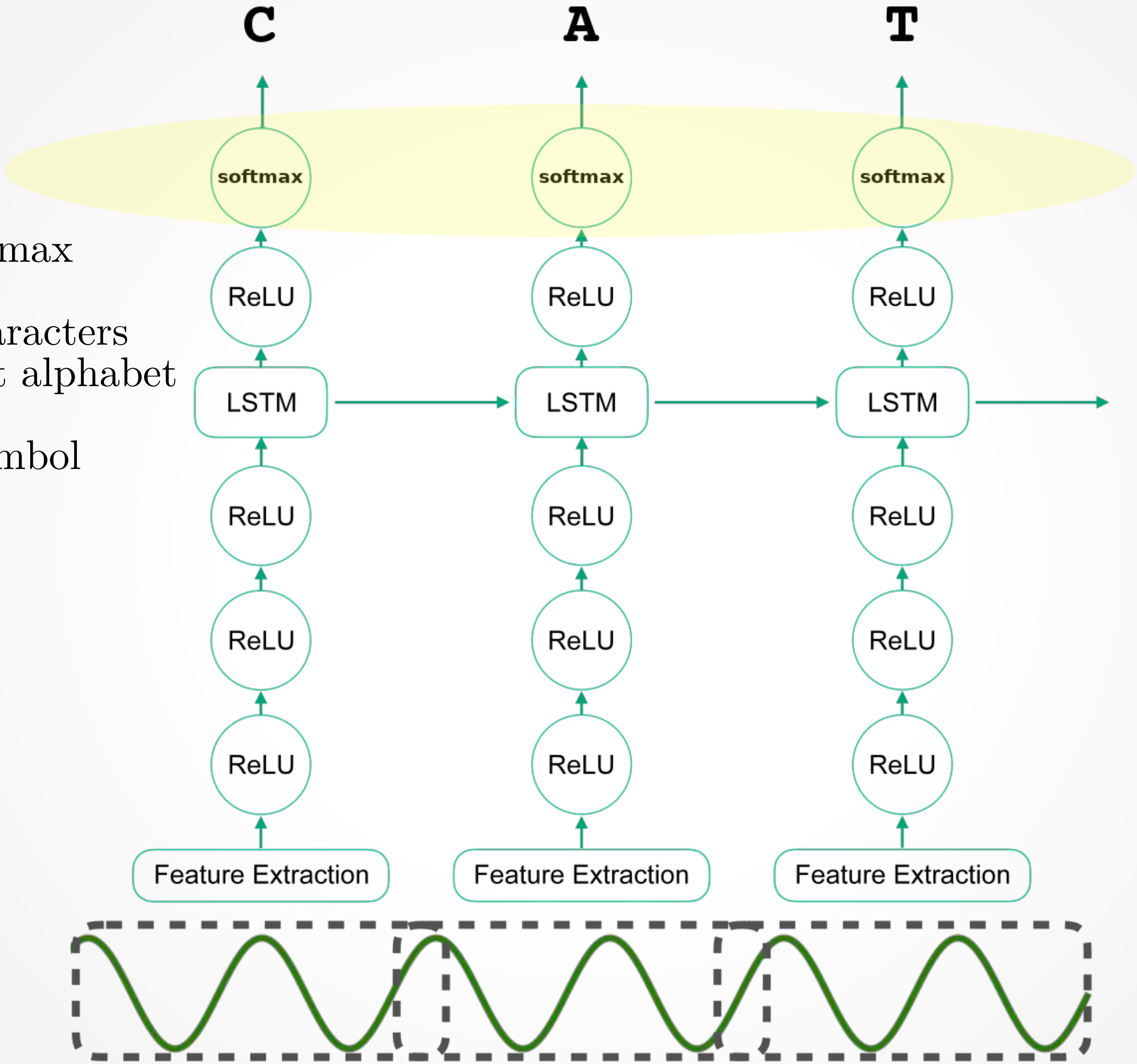
2048 dim FC Layer

Model Architecture

N+1 dims Softmax

N == num characters
in target alphabet

1 == blank symbol


C
A
T
softmax
softmax
softmax
ReLU
ReLU
ReLU
LSTM
LSTM
LSTM
ReLU
ReLU
ReLU
ReLU
ReLU
ReLU
ReLU
ReLU
ReLU
Feature Extraction
Feature Extraction
Feature Extraction