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

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Roadmap

- Overview of Transfer Learning
  - Multi-Task Learning
  - Copy-Paste Transfer
- Multi-Task Learning Studies
  - Linguistic Tasks
  - Engineered Tasks
  - Discovered 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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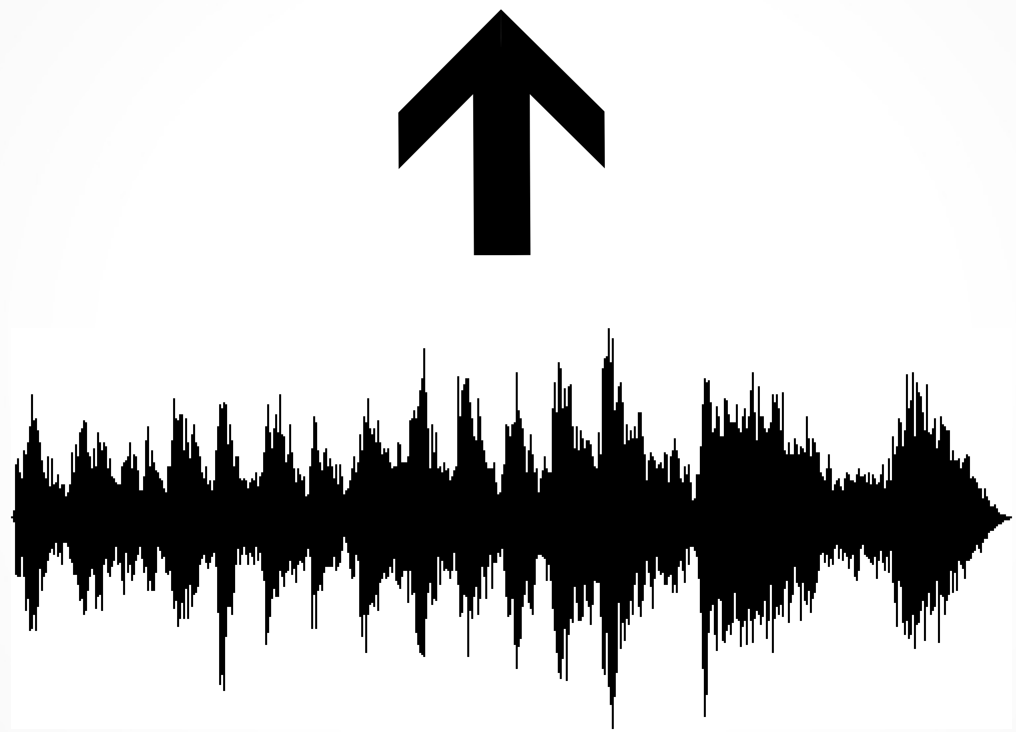
But we can exploit similar use-cases!

Automatic Speech Recognition (ASR)

Automatic Speech Recognition

"THE DOG"



Automatic Speech Recognition

"THE DOG"

TOO 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*

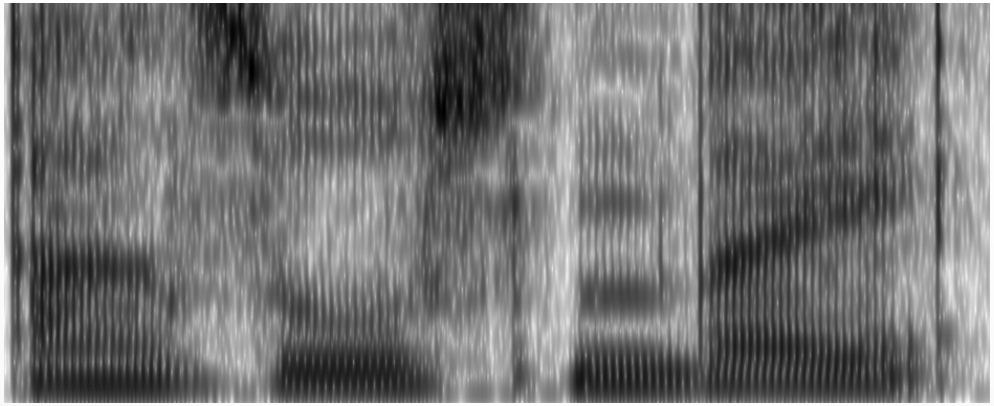
T H E D O G

↑ ← *Acoustic Model*

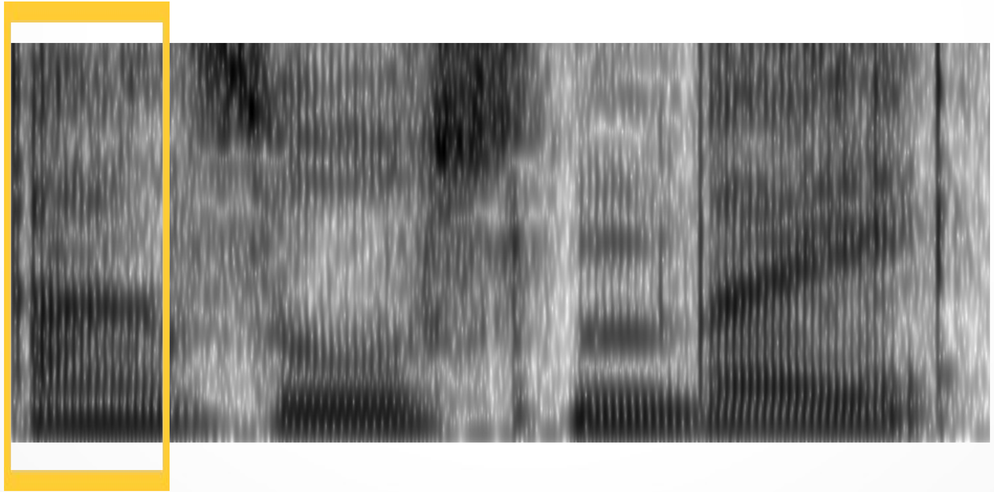
ASR Acoustic Modeling

Acoustic Model

Acoustic Model



Acoustic Model



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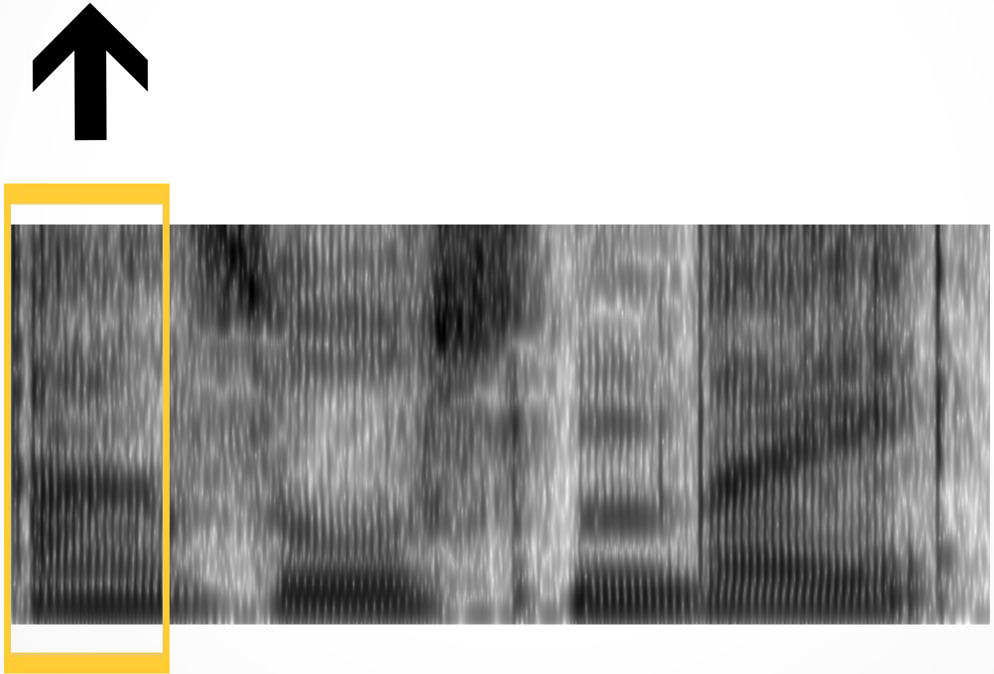

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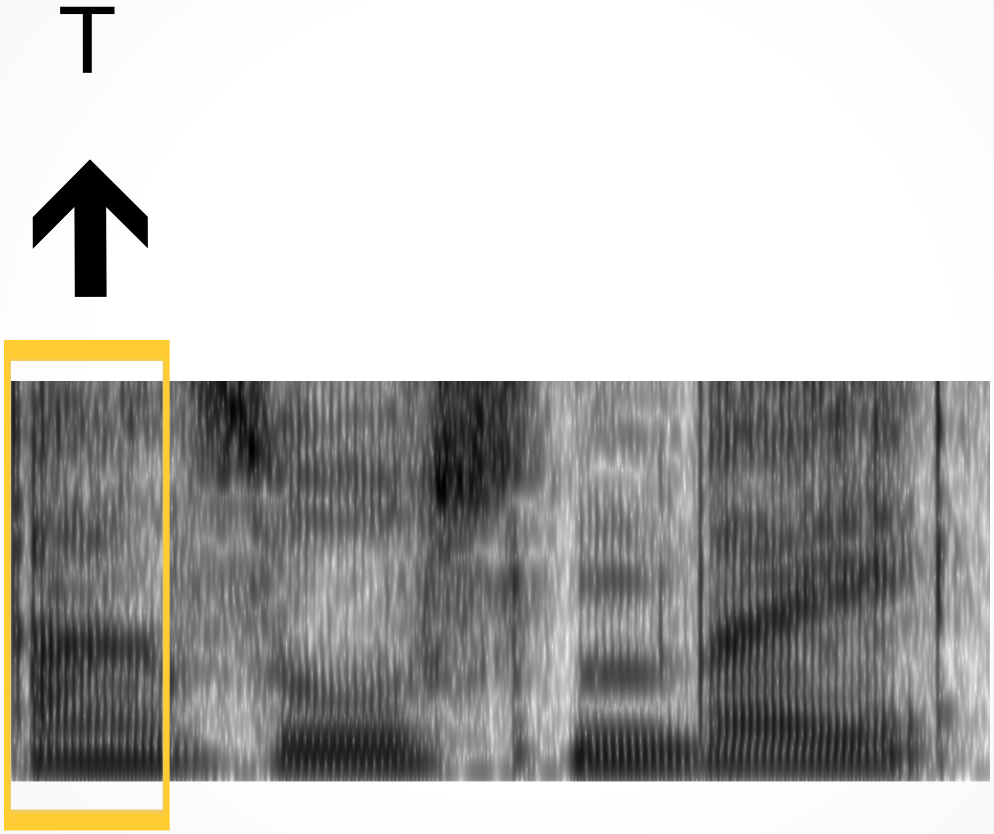

Acoustic Model

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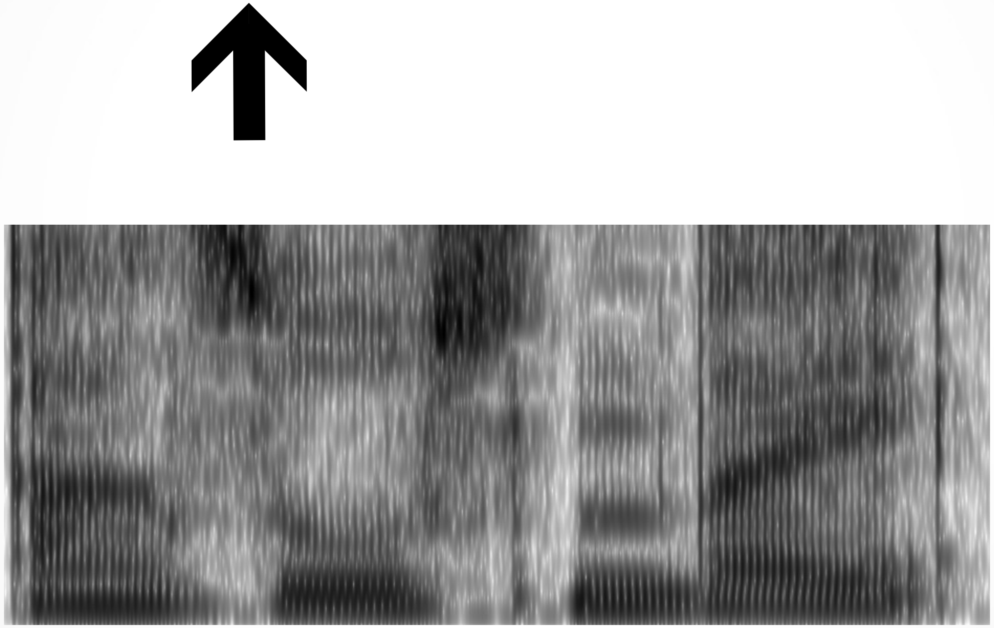

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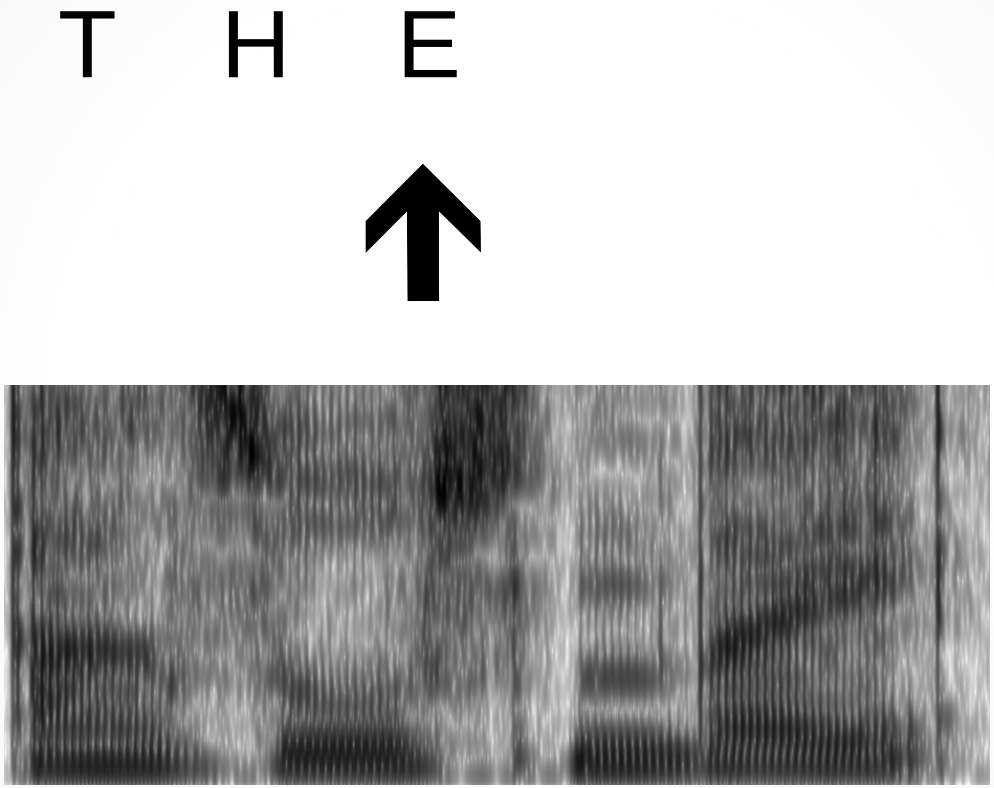

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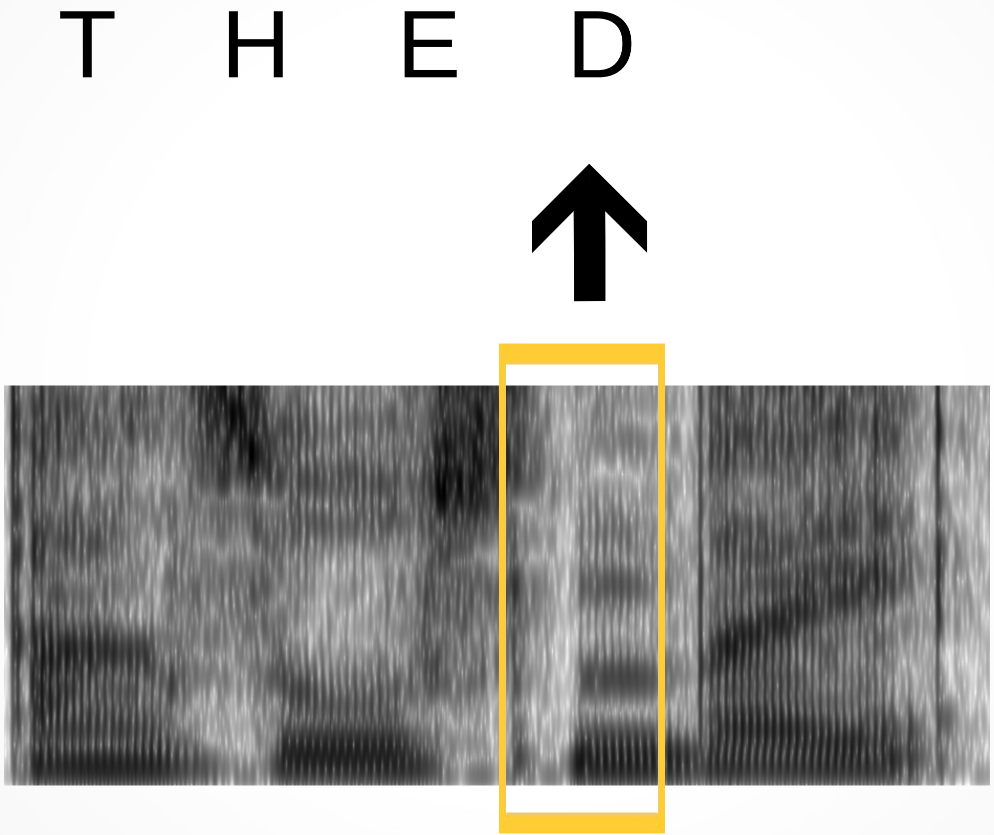

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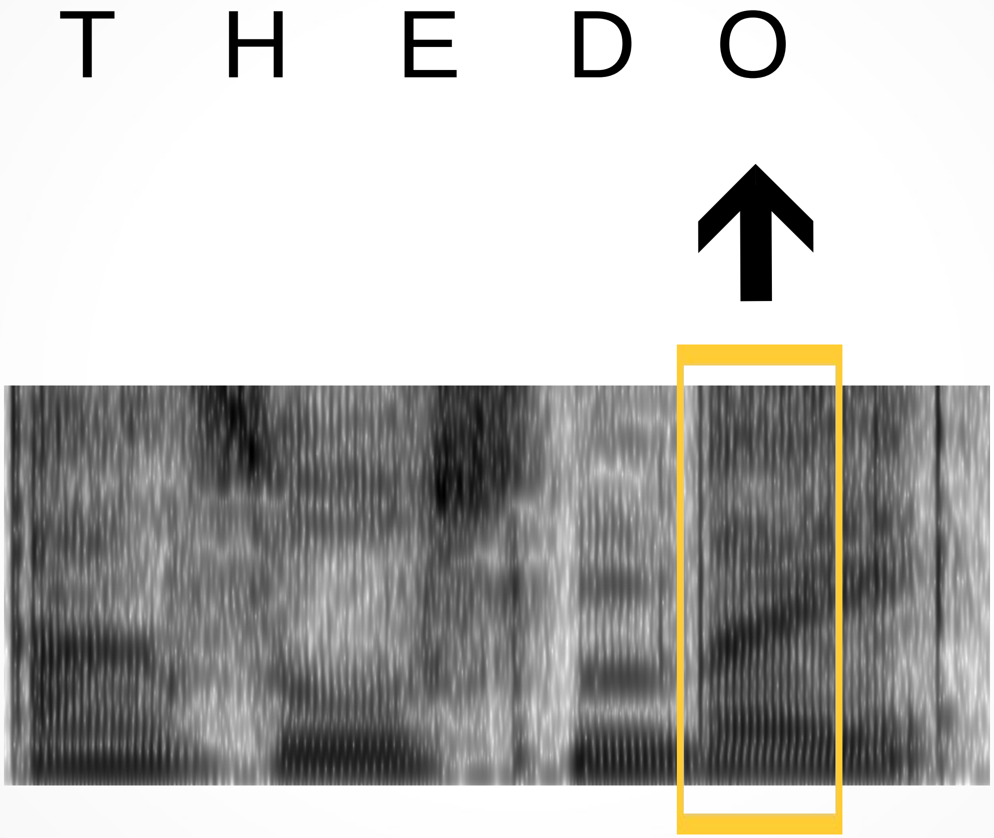
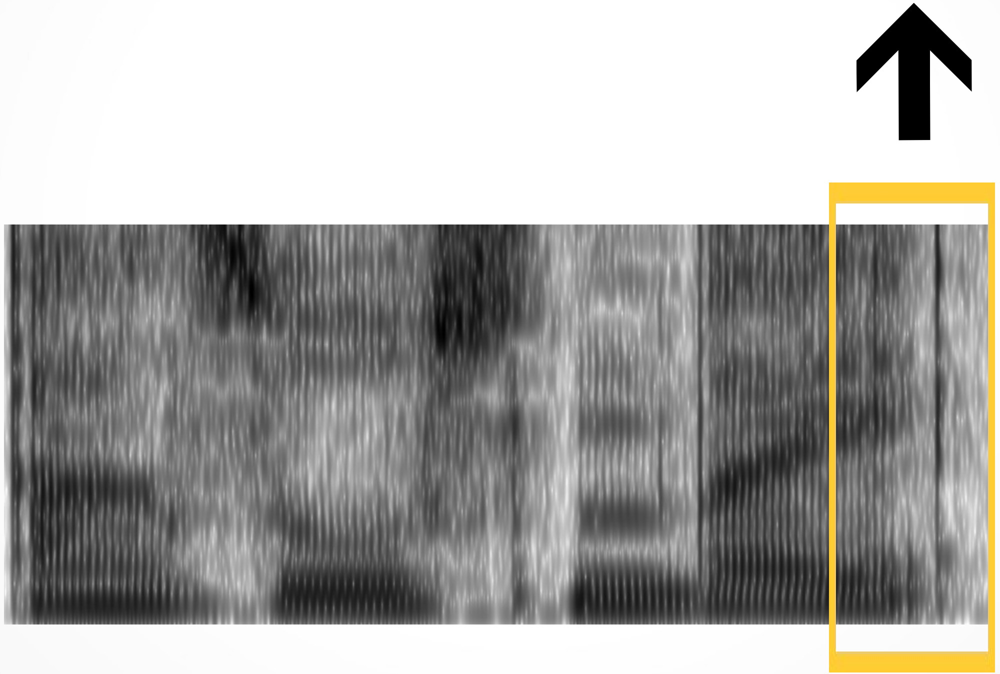


Acoustic Model

T H E D O G



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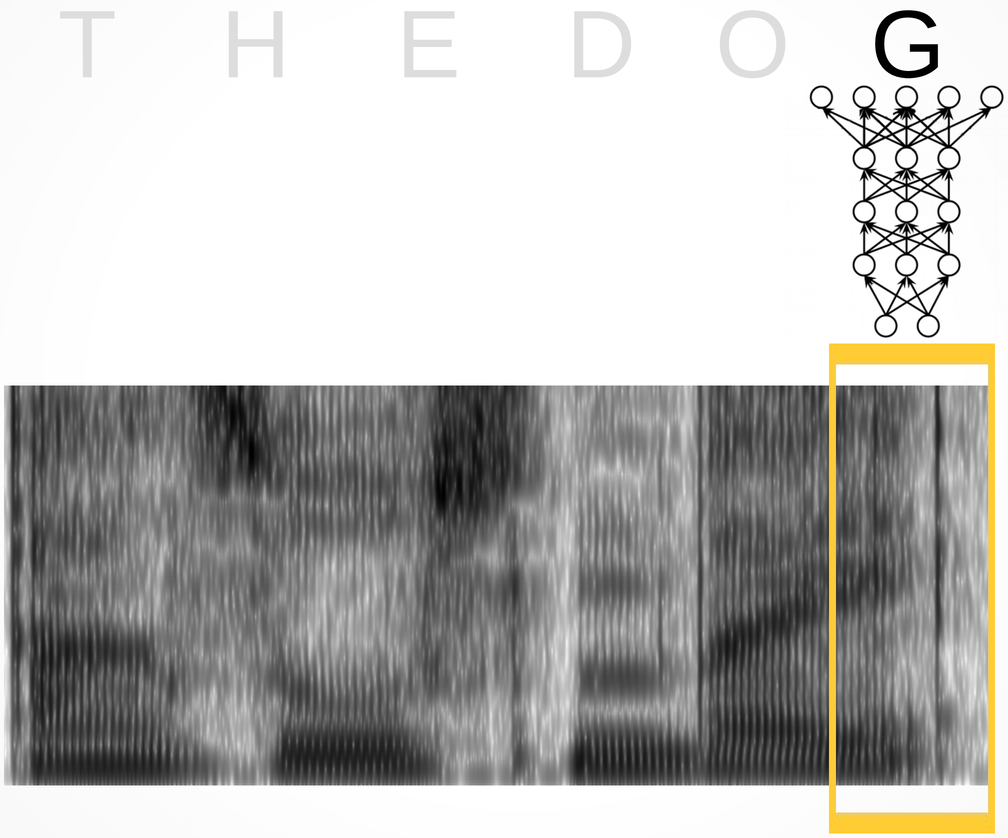

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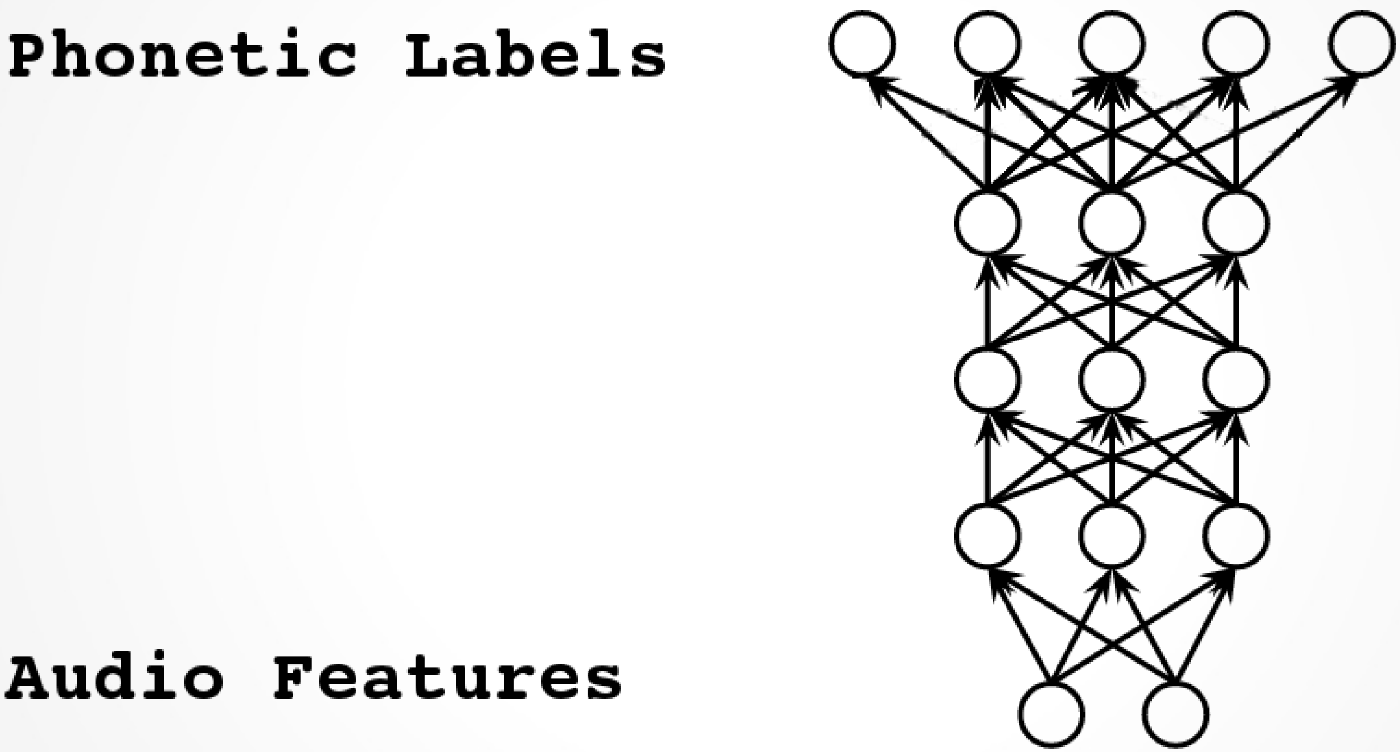
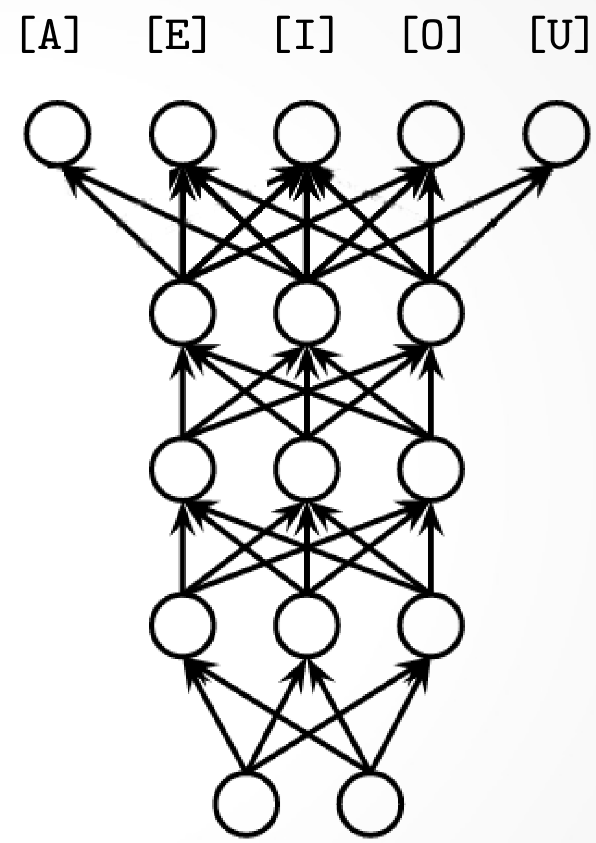


Acoustic Model

Phonetic Labels

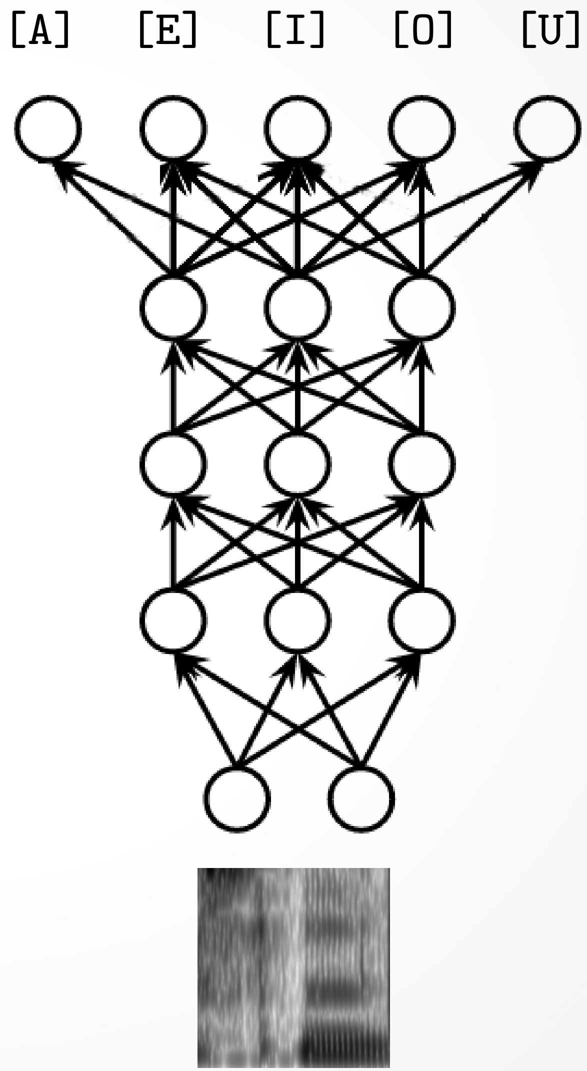
Audio Features



Acoustic Model

Phonetic Labels

Audio Features



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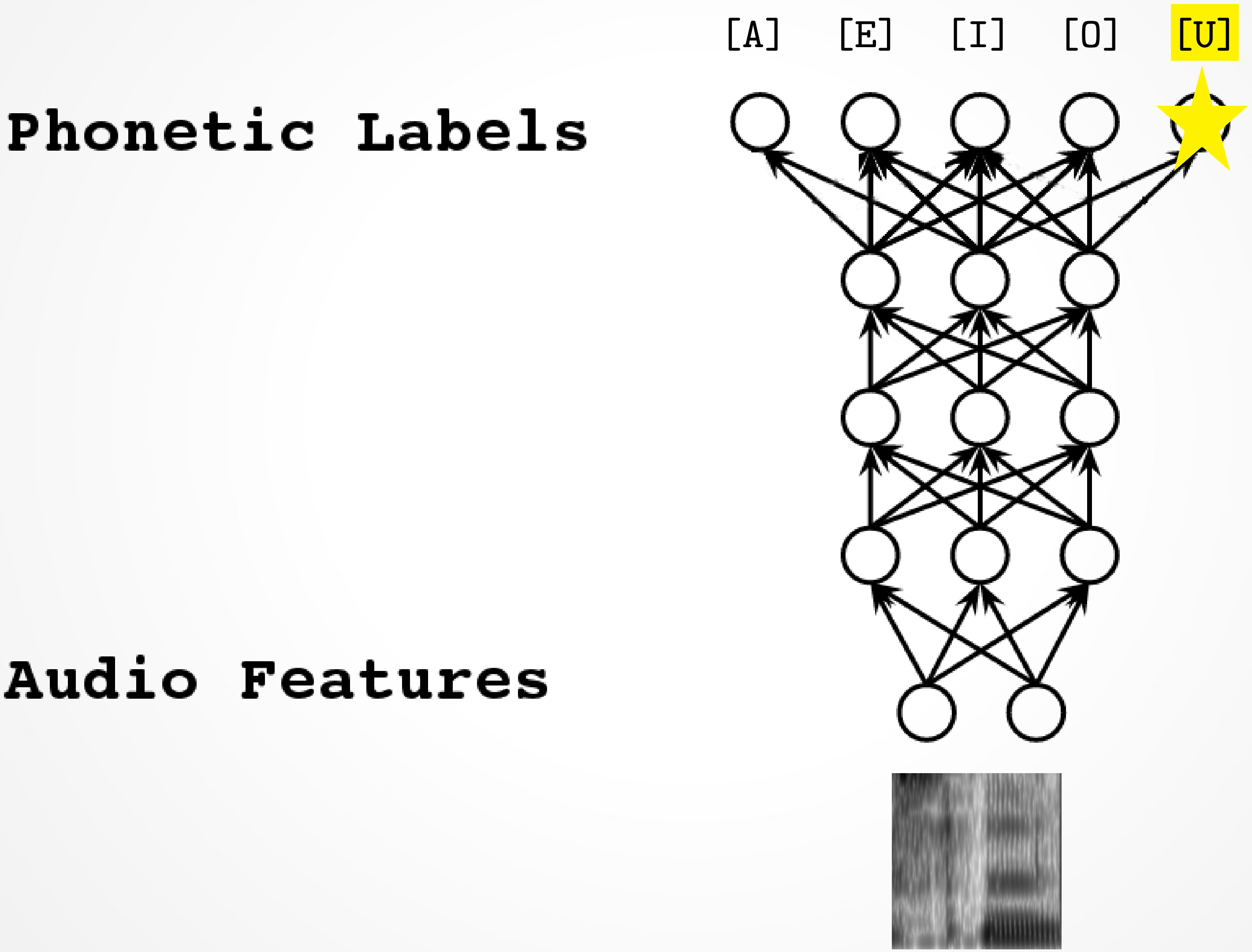

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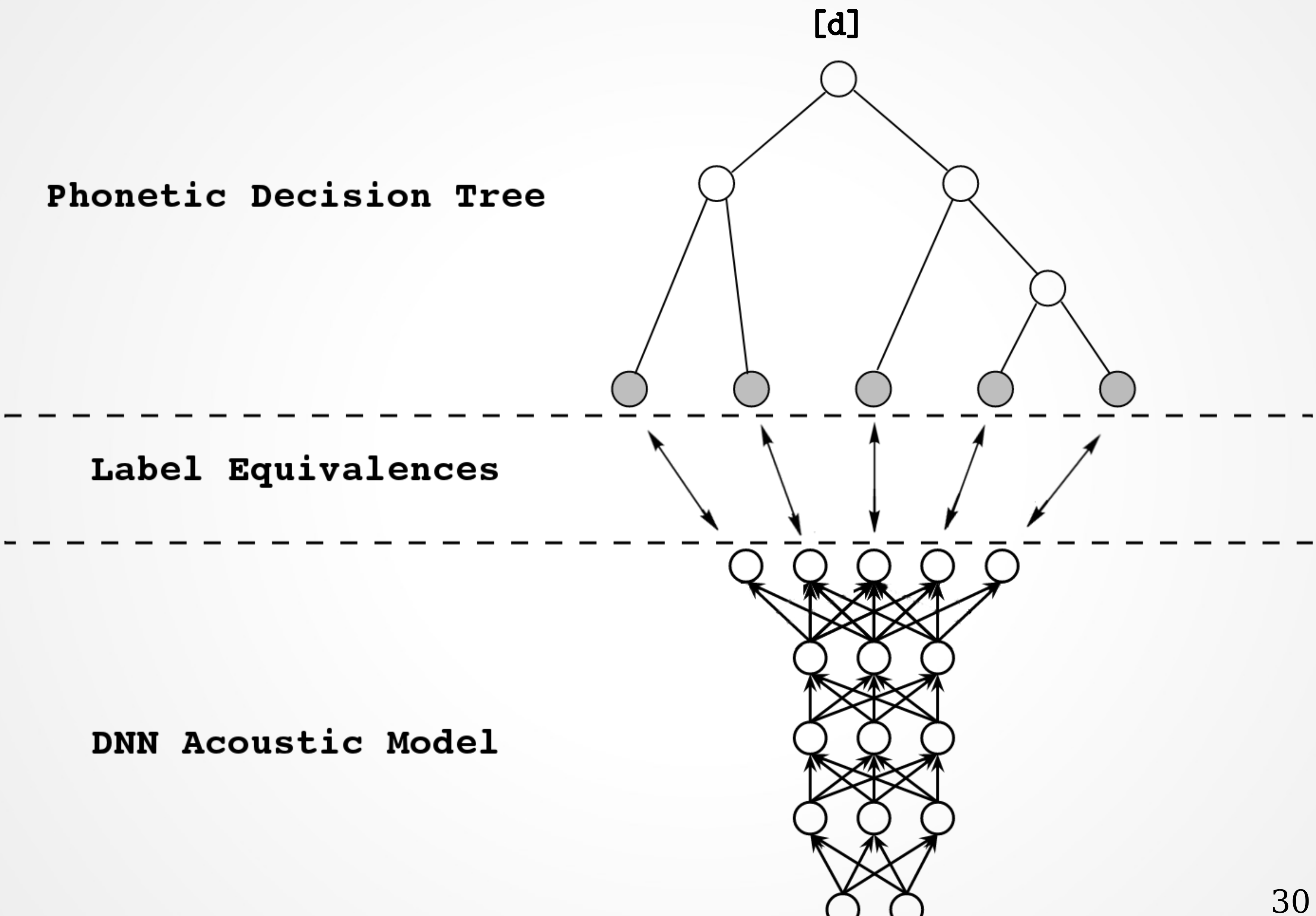


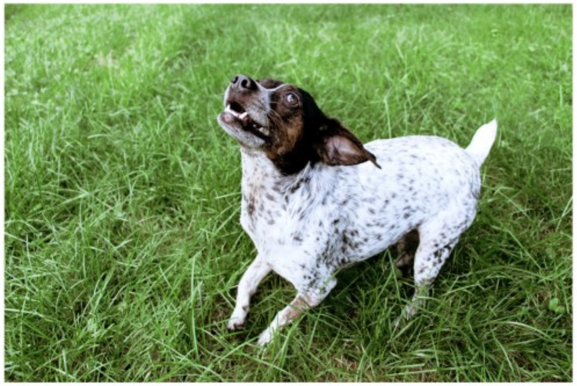
Multi-Task Learning

But first, what is a task?

Single-Task Learning

{rottweiler}

{collie}

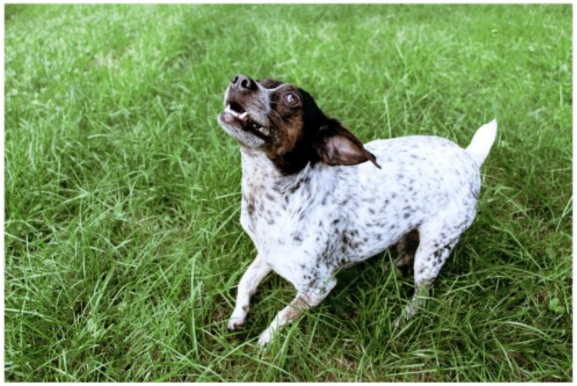


{terrier}

Single-Task Learning

{rottweiler}

{collie}



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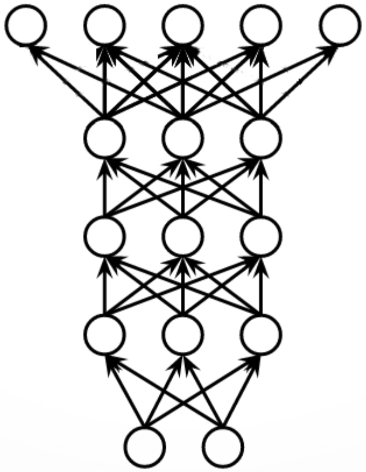

Single-Task Learning

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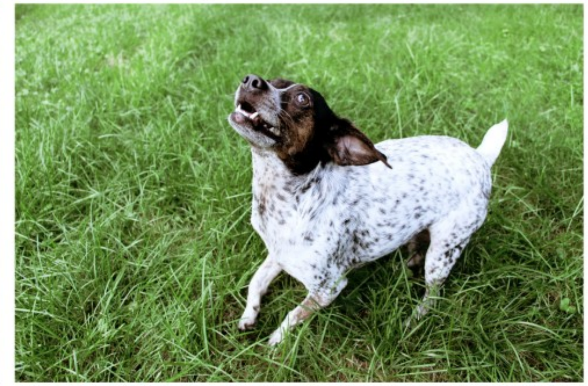

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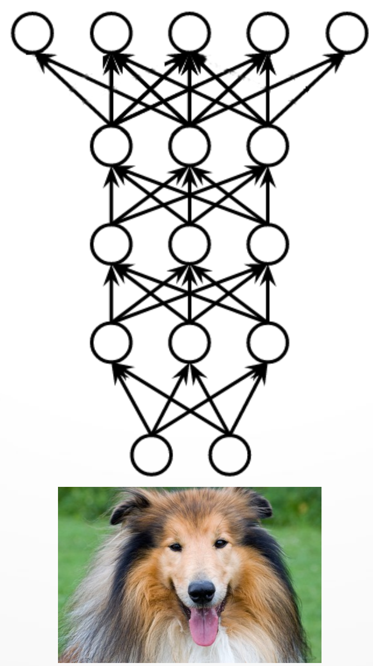

Single-Task Learning

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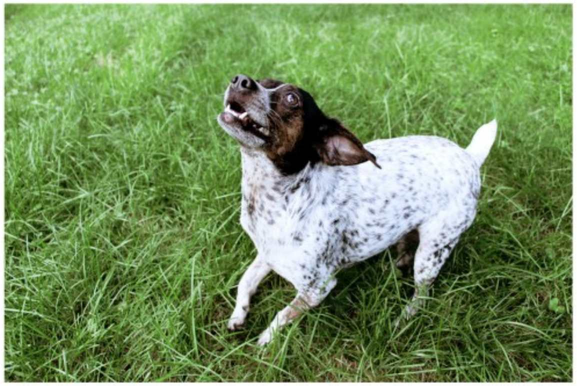
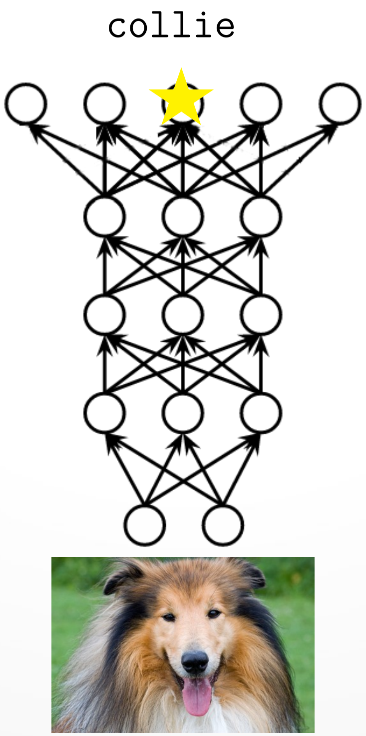


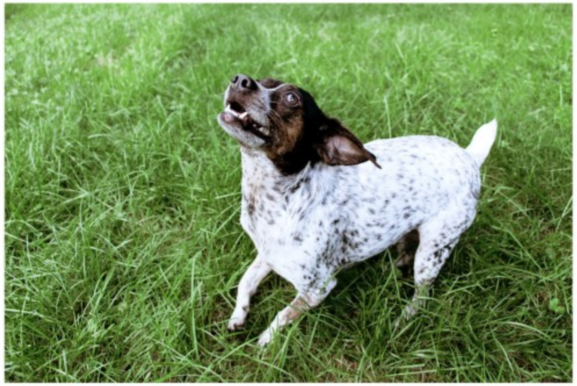
{terrier}



Multi-Task Learning

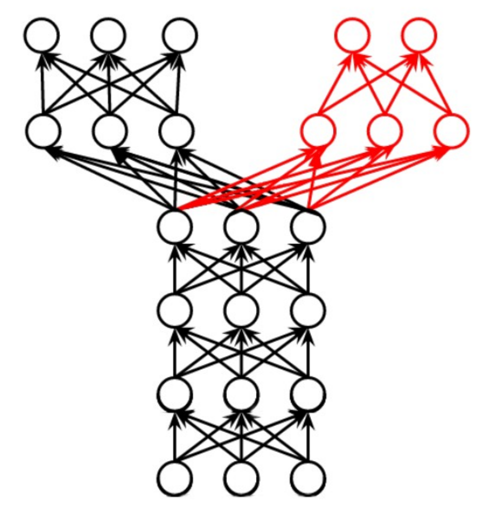
{rottweiler, large}

{collie, large}



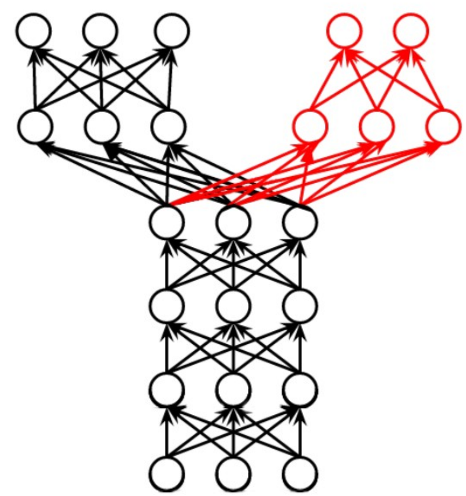
{terrier, small}

Multi-Task Learning



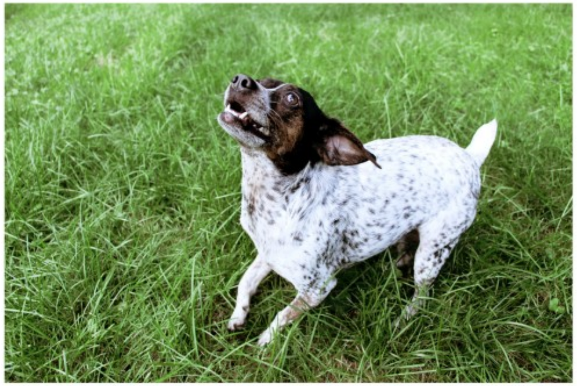
Multi-Task Learning

{rottweiler, large} {collie, large} {terrier, small}

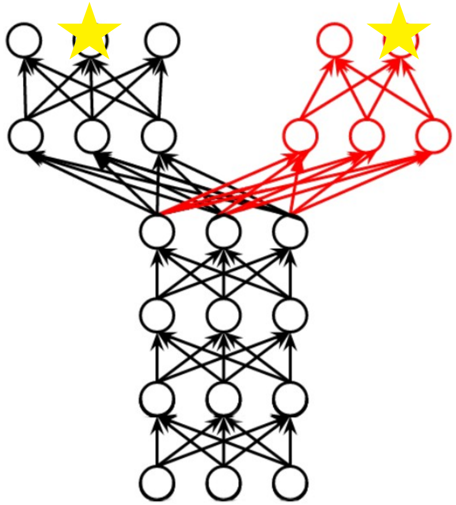


Multi-Task Learning





{rottweiler, large} {collie, large} {terrier, small}



Multi-Task Studies

Linguist-Crafted Tasks

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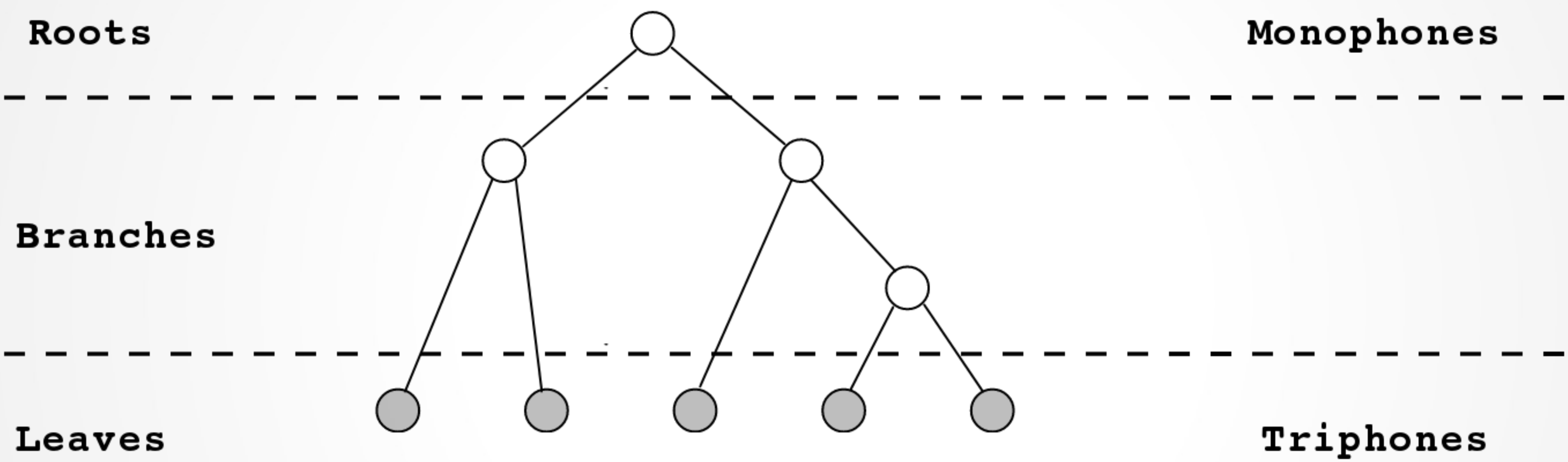

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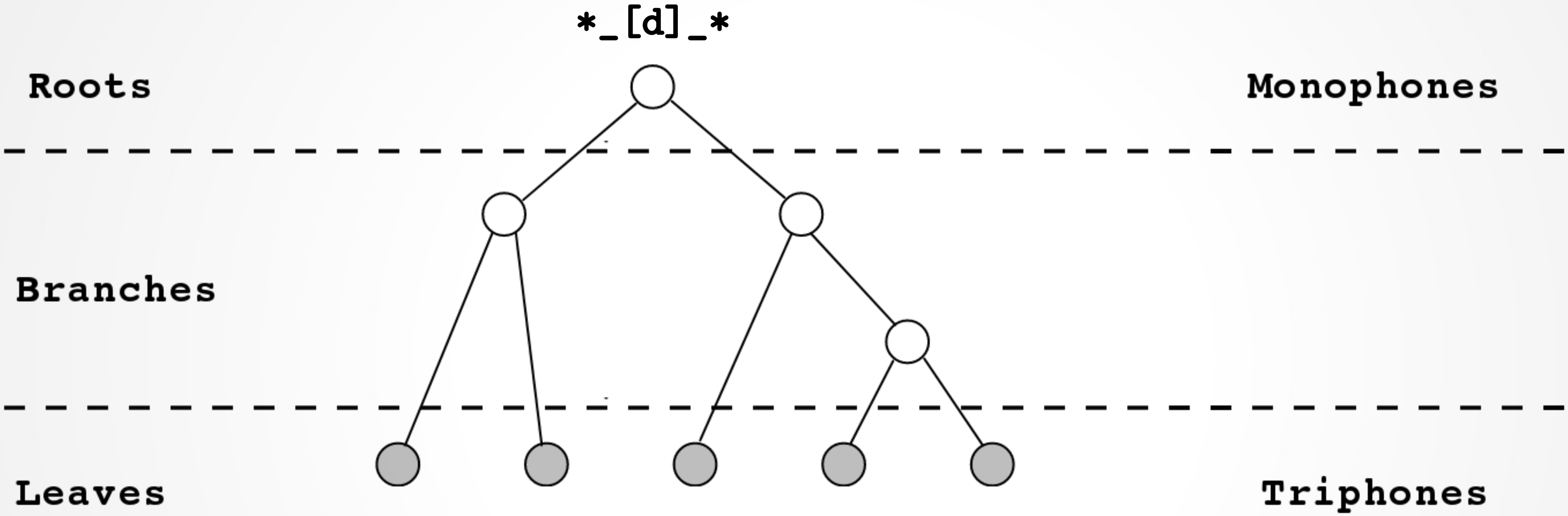

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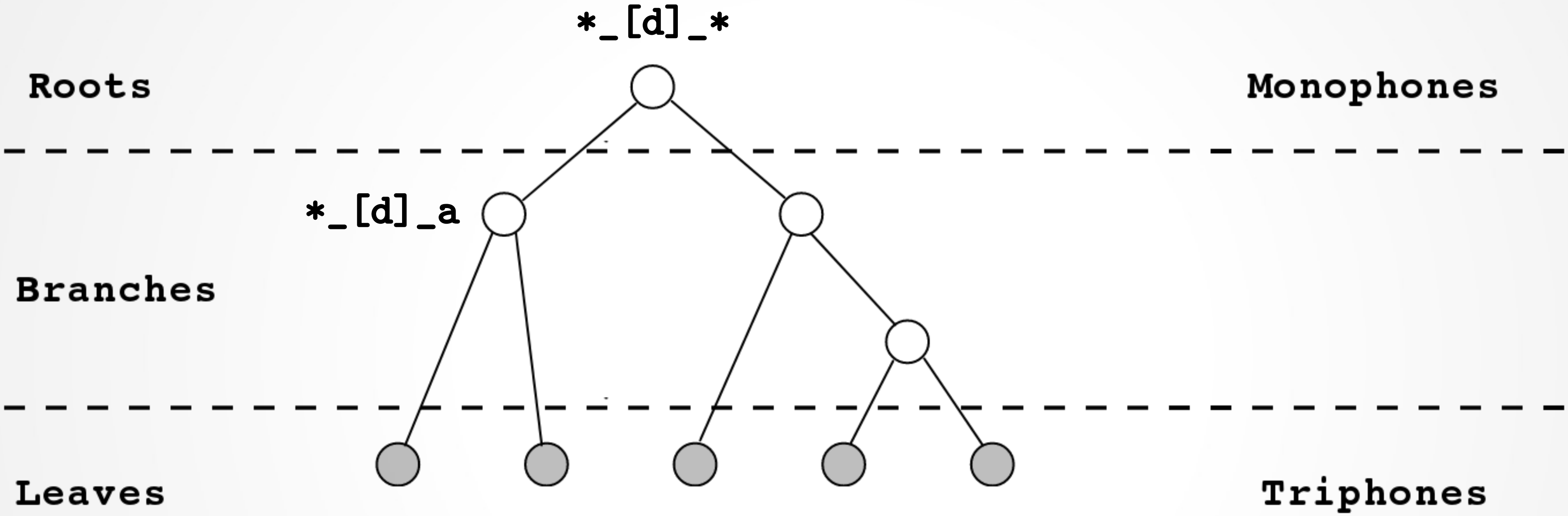

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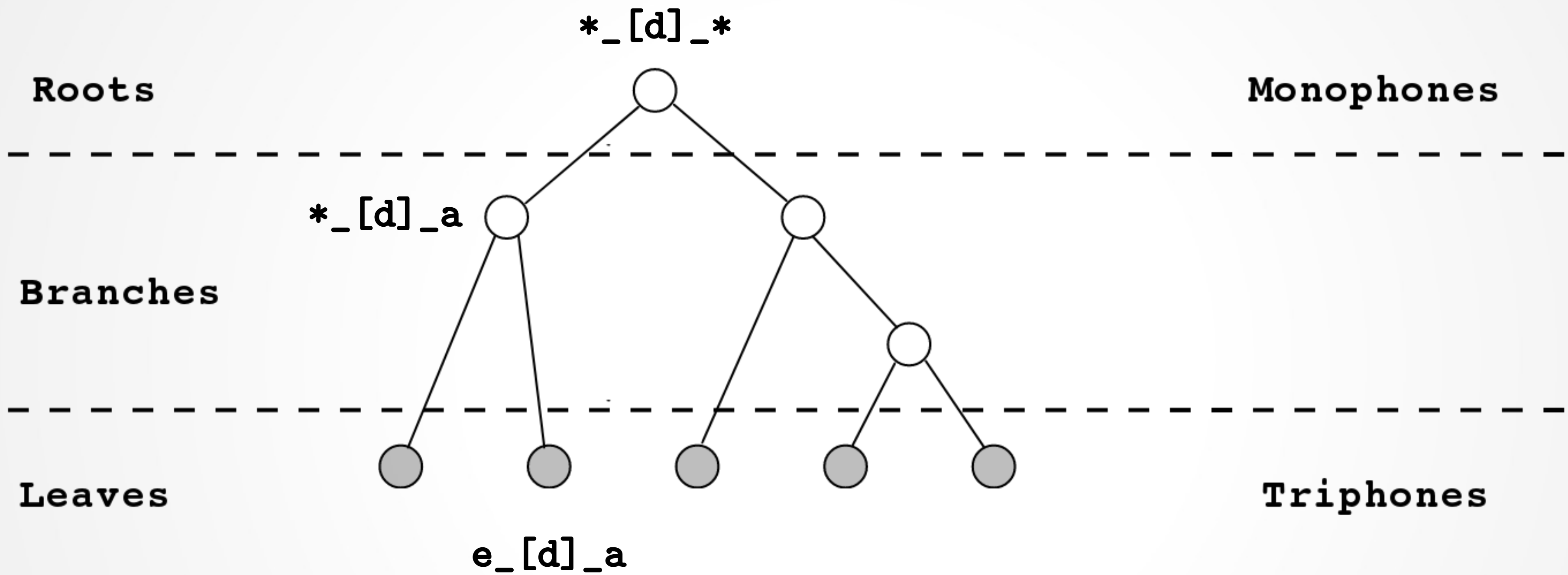

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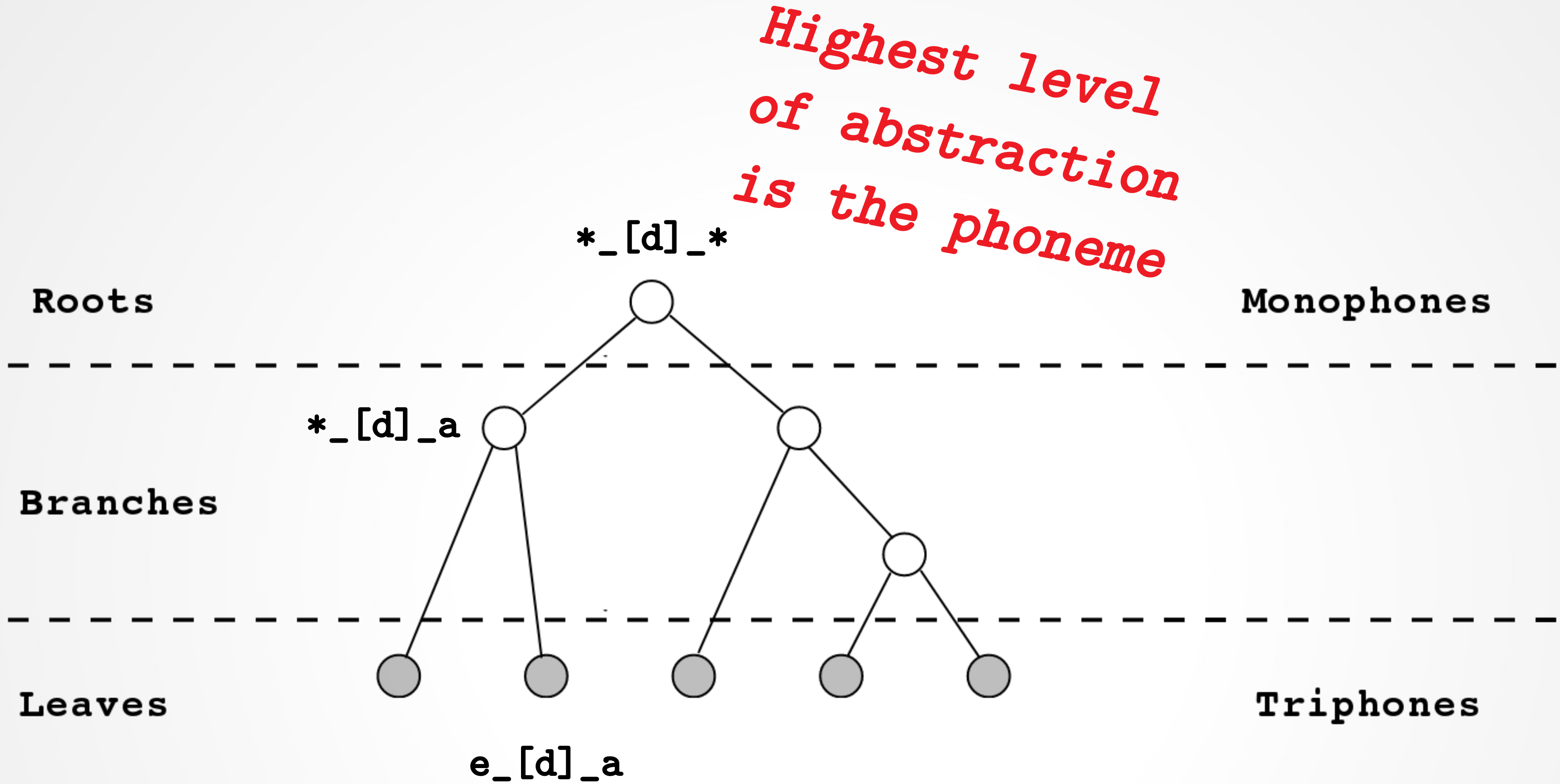

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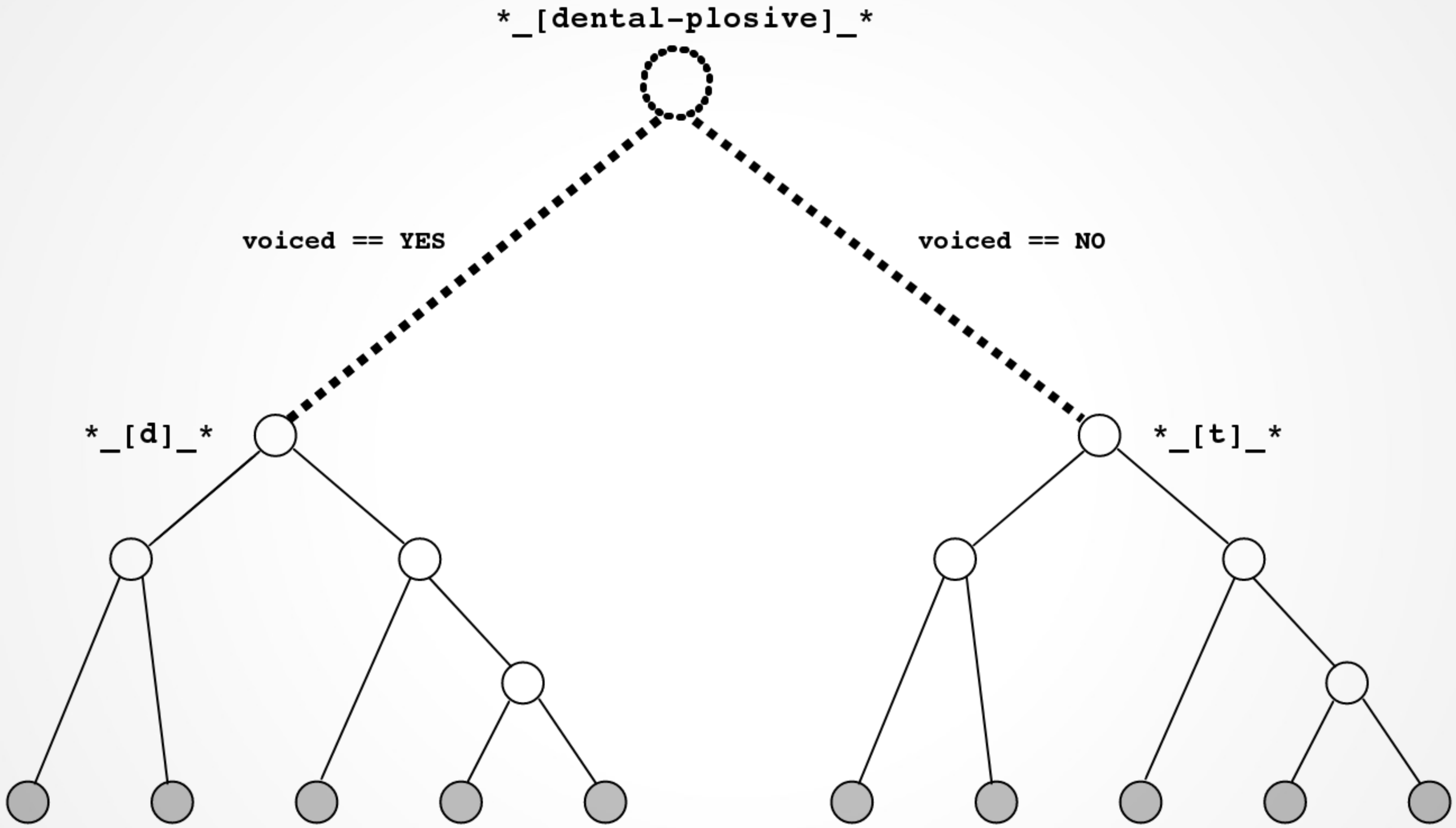
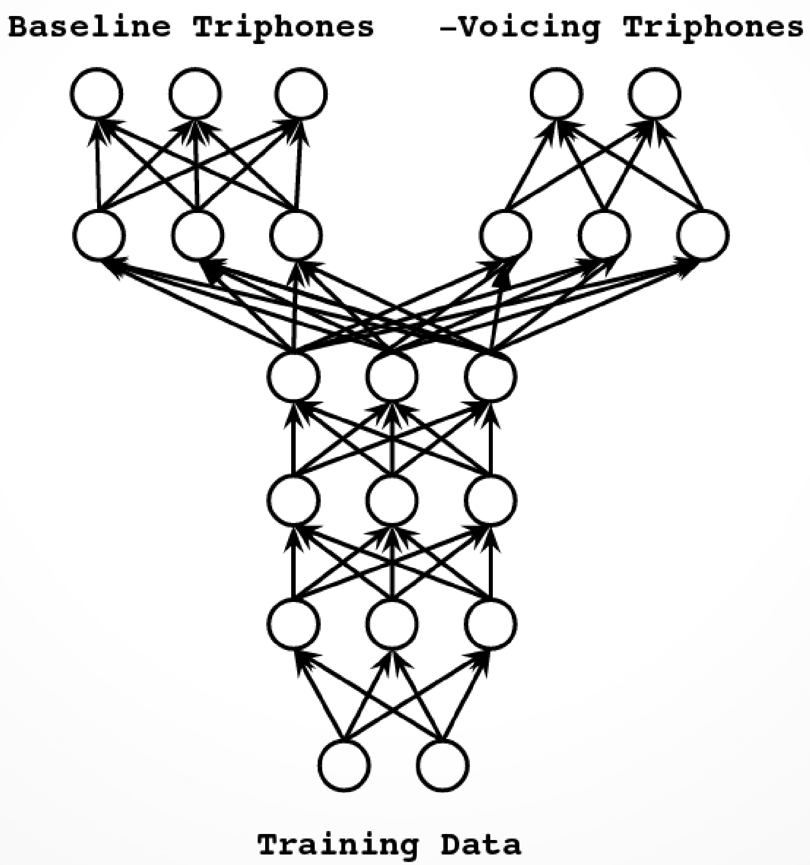


Linguistic Knowledge

	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

Example: Collapsing on Voice



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

Auxiliary Tasks	WER% Triphones	WER% 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 :(

Auxiliary Tasks	WER% Triphones	WER% Monophones
STL Baseline	41.67	
Voice	**41.16**	42.36
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Monolingual Experiments

The main task is more important...

Monolingual Experiments

The main task is more important...

Implement a relative weighting!

Monolingual Experiments

Auxiliary Tasks	WER% Triphones	WER% Monophones
STL Baseline	41.67	
Voice	**41.00**	**40.43**
Place	**41.37**	**41.46**
Manner	**40.43**	**41.34**
Voice + Place	**41.31**	**41.28**
Voice + Manner	**41.25**	42.18
Place + Manner	42.03	42.48
Voice + Manner + Place	**41.64**	41.88

Monolingual Experiments

Now, that looks better :)

Auxiliary Tasks	WER% Triphones	WER% Monophones
STL Baseline	41.67	
Voice	**41.00**	**40.43**
Place	**41.37**	**41.46**
Manner	**40.43**	**41.34**
Voice + Place	**41.31**	**41.28**
Voice + Manner	**41.25**	42.18
Place + Manner	42.03	42.48
Voice + Manner + Place	**41.64**	41.88

Multilingual Experiments

Multilingual Experiments

Not so great :(

Auxiliary Tasks	WER% Triphones	WER% 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

Now, that looks better :)

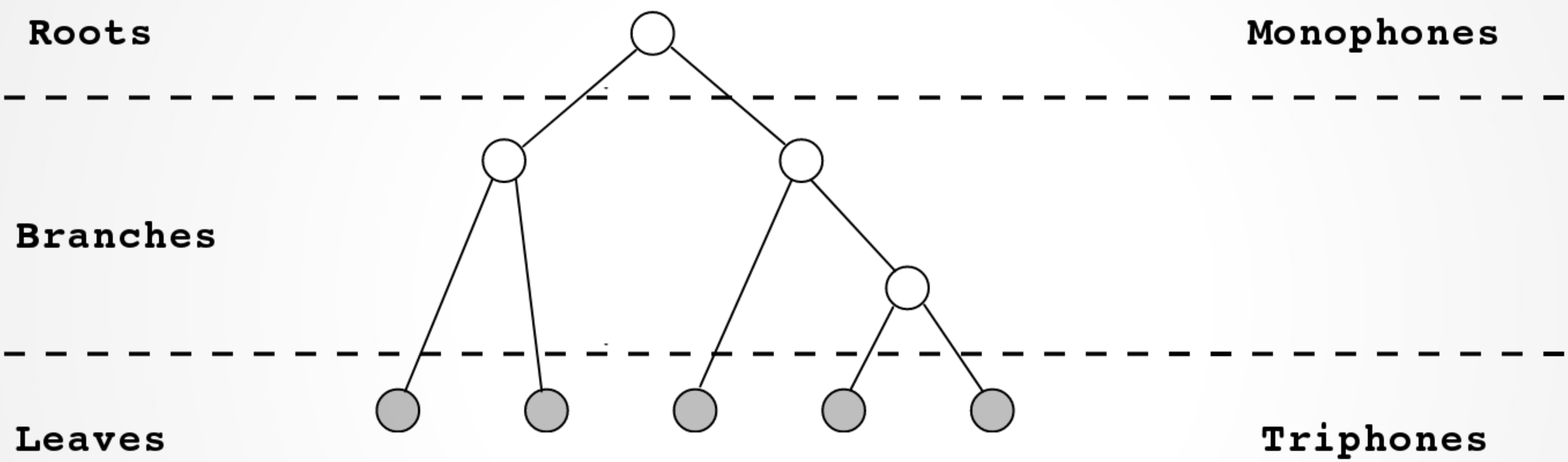
Auxiliary Tasks	WER% Triphones	WER% Monophones
STL Baseline	53.07	
Phonemes	**51.80**	**51.61**
Voice	**52.39**	53.46
Place	**51.90**	**52.29**
Manner	**52.00**	**51.80**
Voice + Place	**52.68**	**52.78**
Voice + Manner	**51.22**	**51.32**
Place + Manner	**50.83**	53.66
Voice + Manner + Place	**52.78**	**52.39**

Engineered Tasks

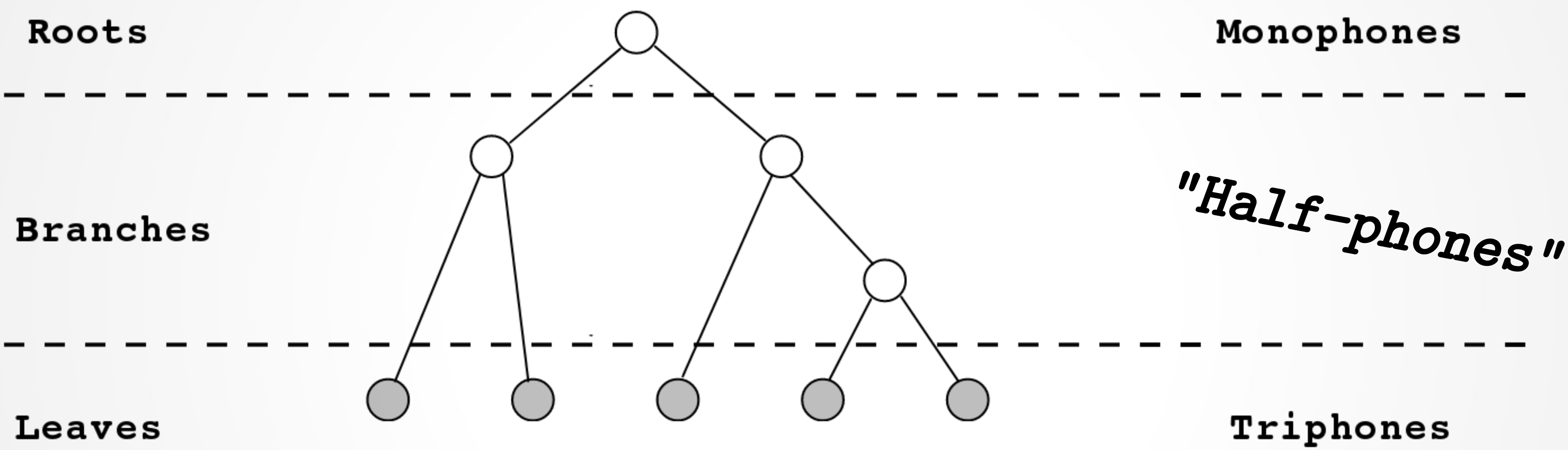
Engineered Tasks

Can we find linguistic bias without a linguist?

Linguist-Crafted Tasks



Linguist-Crafted Tasks



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

DNN Training Procedure

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

DNN Training Procedure

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

Engineered Tasks

Auxiliary (Source Lang) Tasks	Source:Target Weighting *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**

Discovered Tasks

Discovered Tasks

Can we find linguistic bias without a phonetic tree?

Discovered Tasks

Discovered Tasks

	$\alpha = 0.1$	$\alpha = 0.2$	$\alpha = 0.3$
Single Task Baseline		57.55 $\pm$1.82	
+ **256 clusters**	57.93 $\pm$1.63	57.04 $\pm$1.58	57.66 $\pm$1.24
+ **1024 clusters**	57.69 $\pm$3.78	**56.99** $\pm$3.08	57.60 $\pm$0.79
+ **4096 clusters**	57.25 $\pm$2.87	58.07 $\pm$1.35	57.45 $\pm$0.32

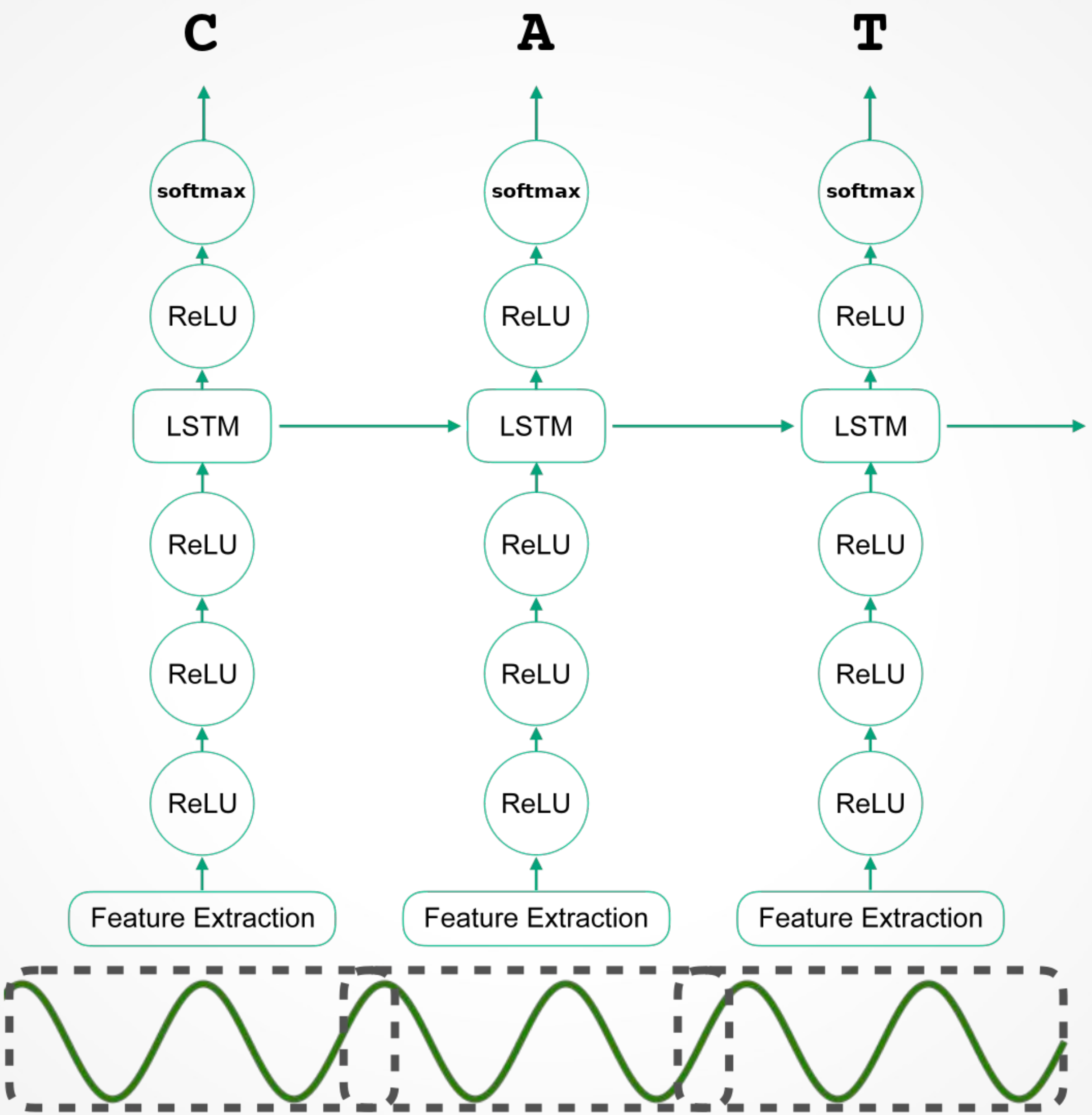
Discovered Tasks

	$\alpha = 0.1$	$\alpha = 0.2$	$\alpha = 0.3$
Single Task Baseline		57.55 ± 1.82	
+ **256 clusters**	57.33 ± 2.49	58.02 ± 2.09	57.18 ± 0.56
+ **1024 clusters**	57.74 ± 3.06	**56.88** ± 1.33	57.13 ± 1.55
+ **4096 clusters**	57.56 ± 2.53	57.49 ± 3.17	57.31 ± 1.31

End-to-End Transfer Studies

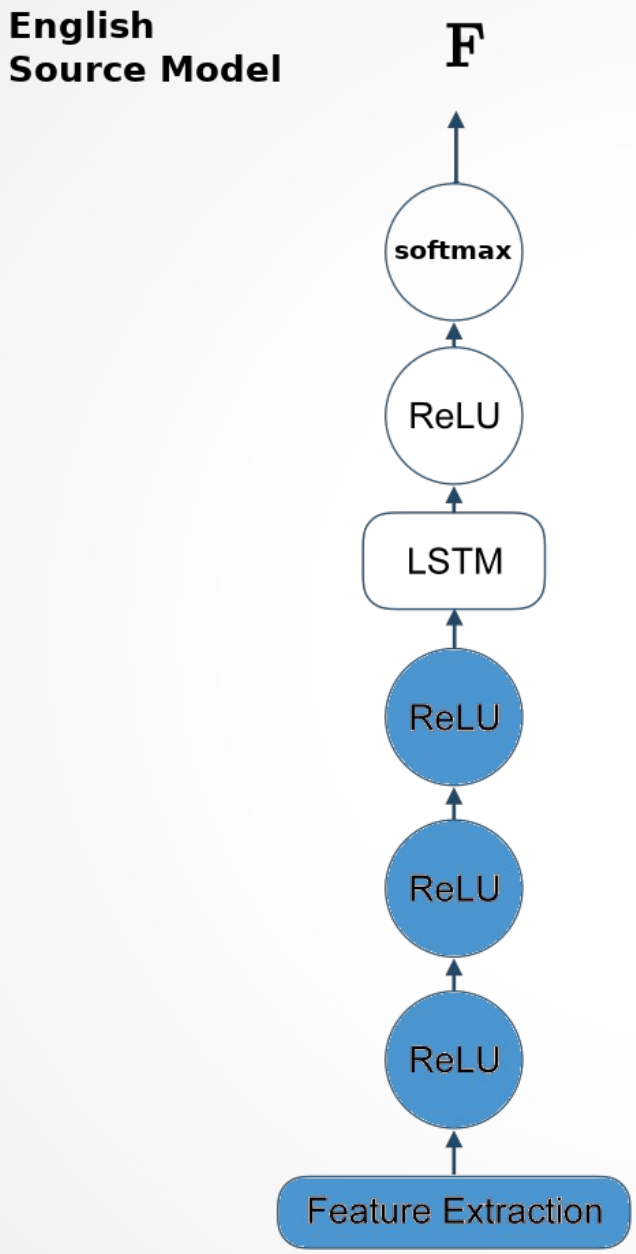
DeepSpeech: Model Architecture

DeepSpeech: Model Architecture

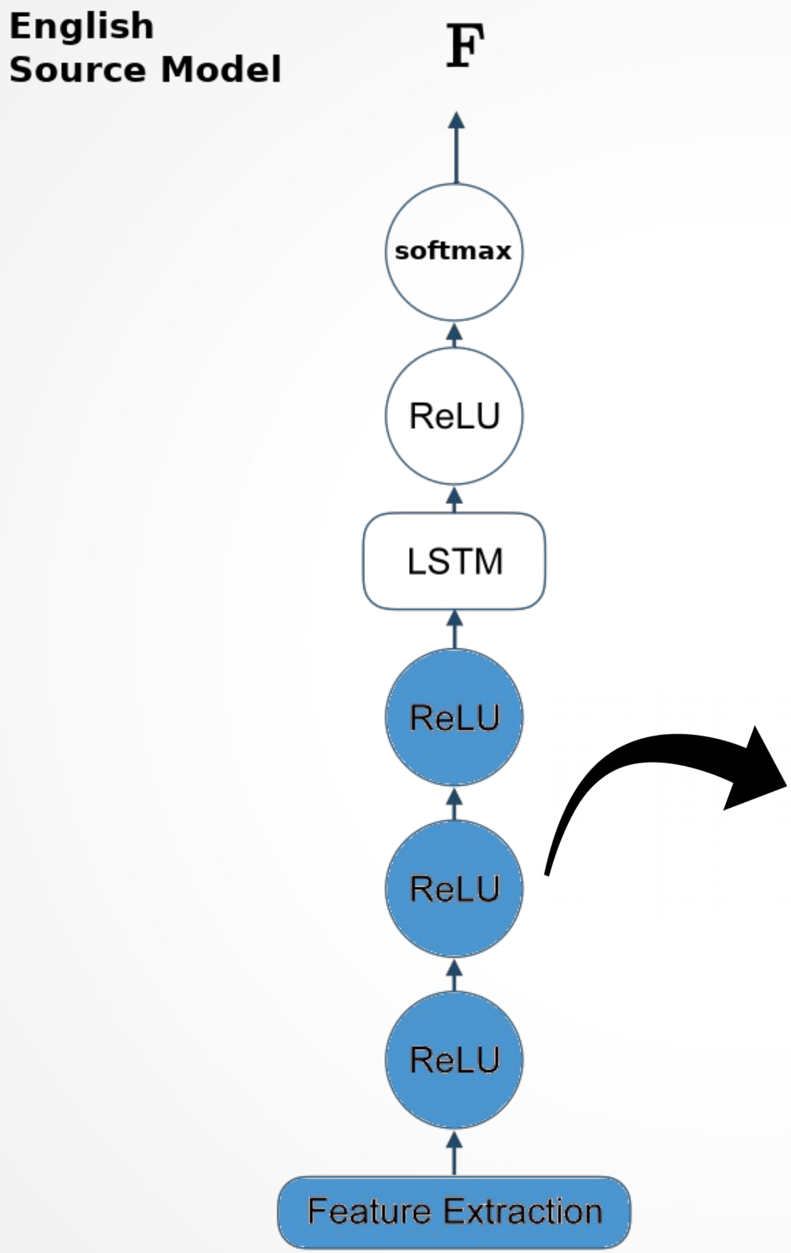


Transfer Experiments on ASR

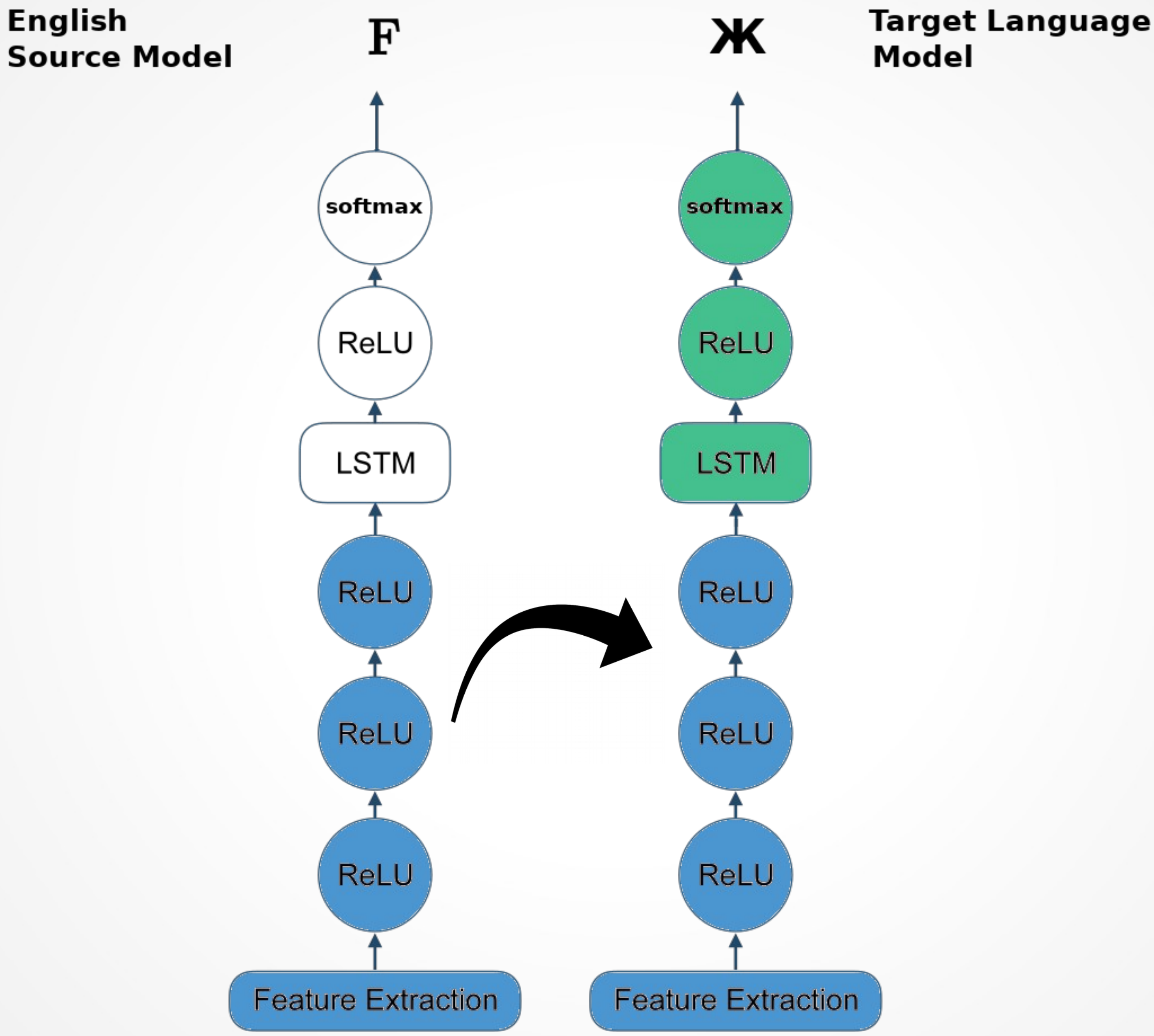
CTC Transfer Experiments



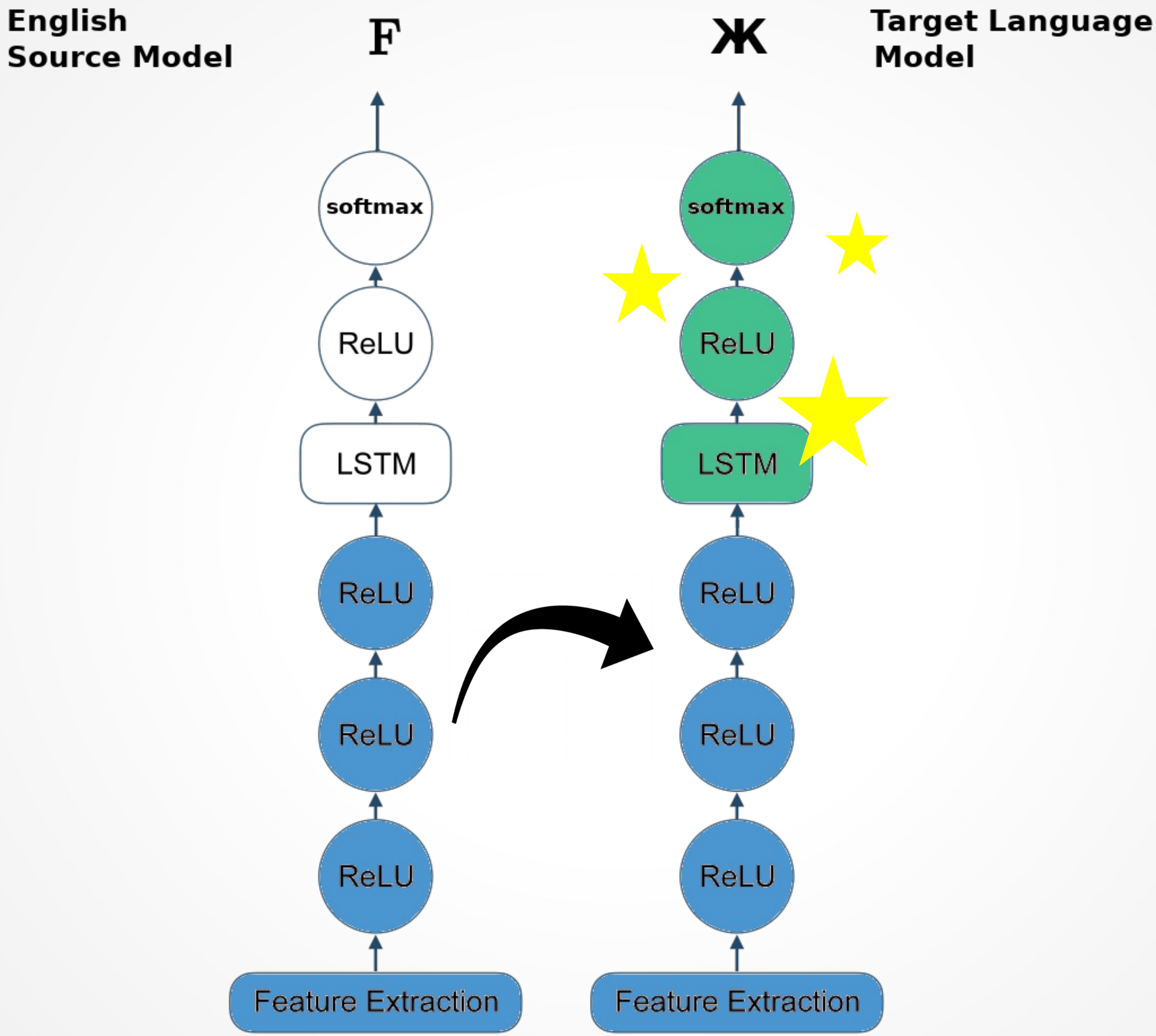
CTC Transfer Experiments



CTC Transfer Experiments



CTC Transfer Experiments



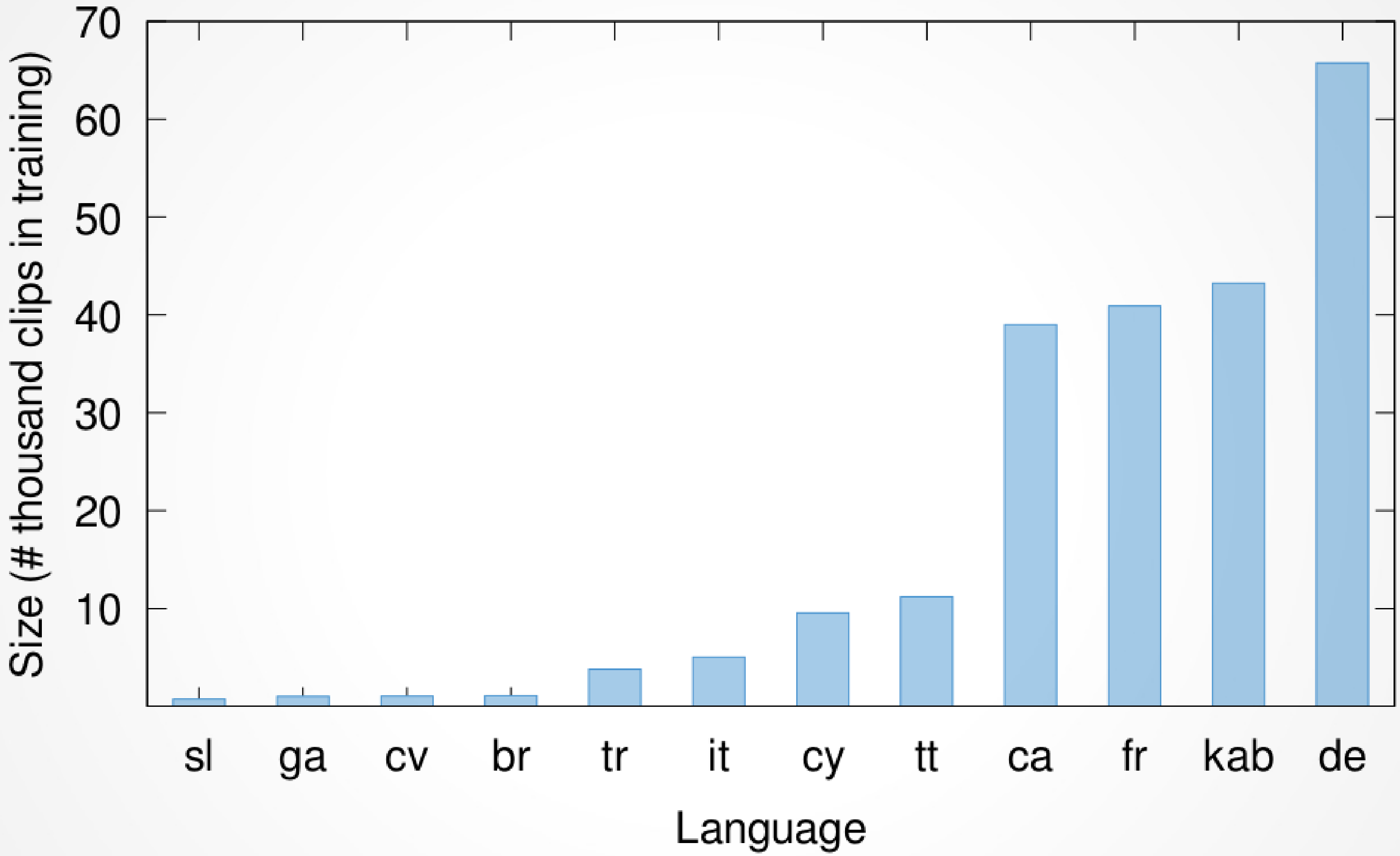
Experimental Design

- 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 (Spoken Corpora)



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**

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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

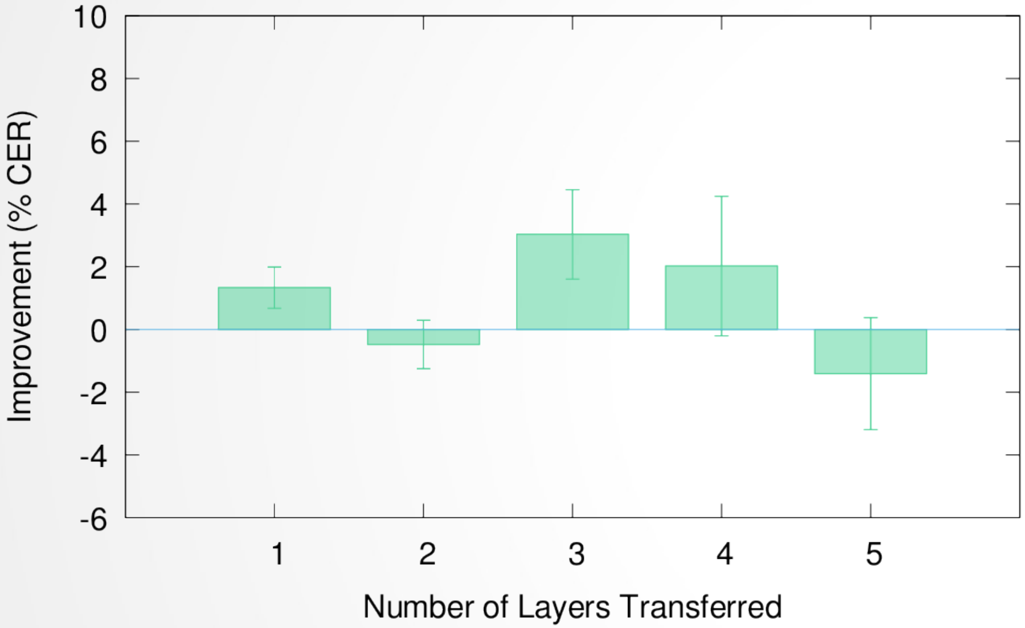
Table 3. Fine-Tuned Transfer Learning Character-error rates (CER)

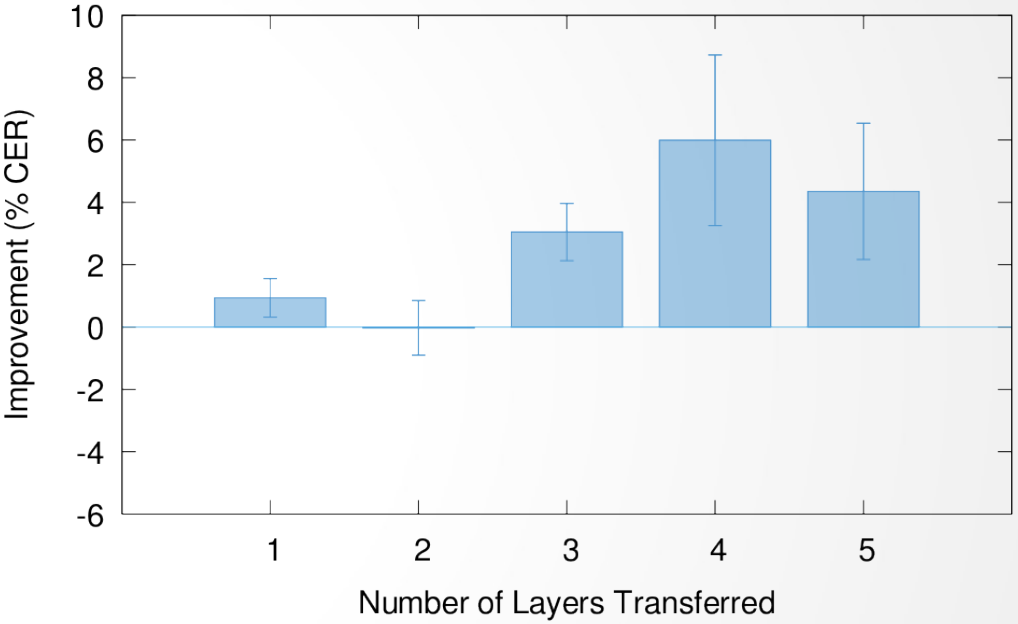
Fine-Tuning Transfer Results

	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

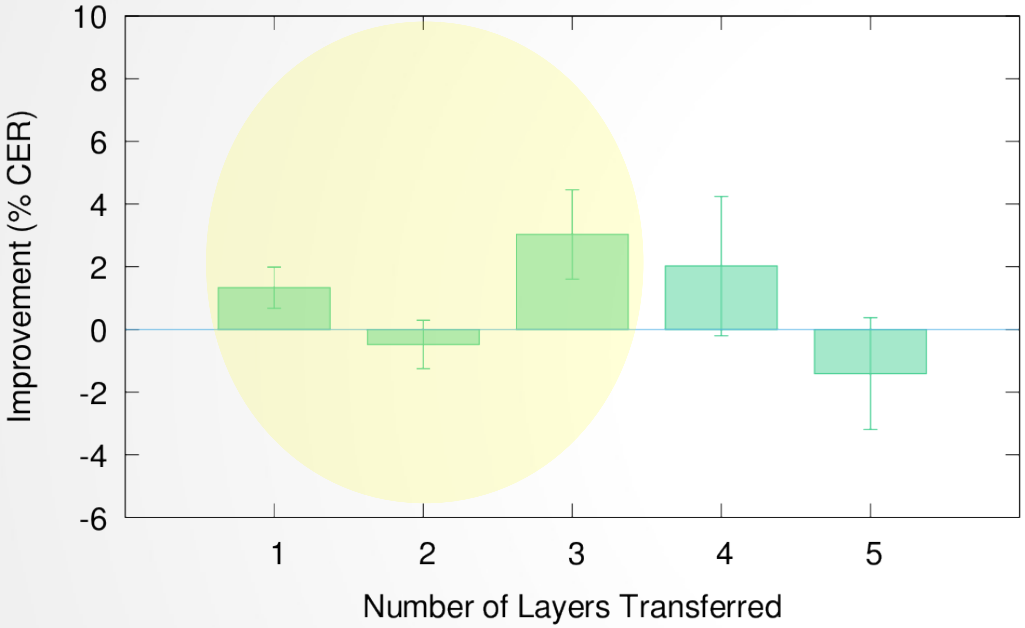
Table 3. Fine-Tuned Transfer Learning Character-error rates (CER)

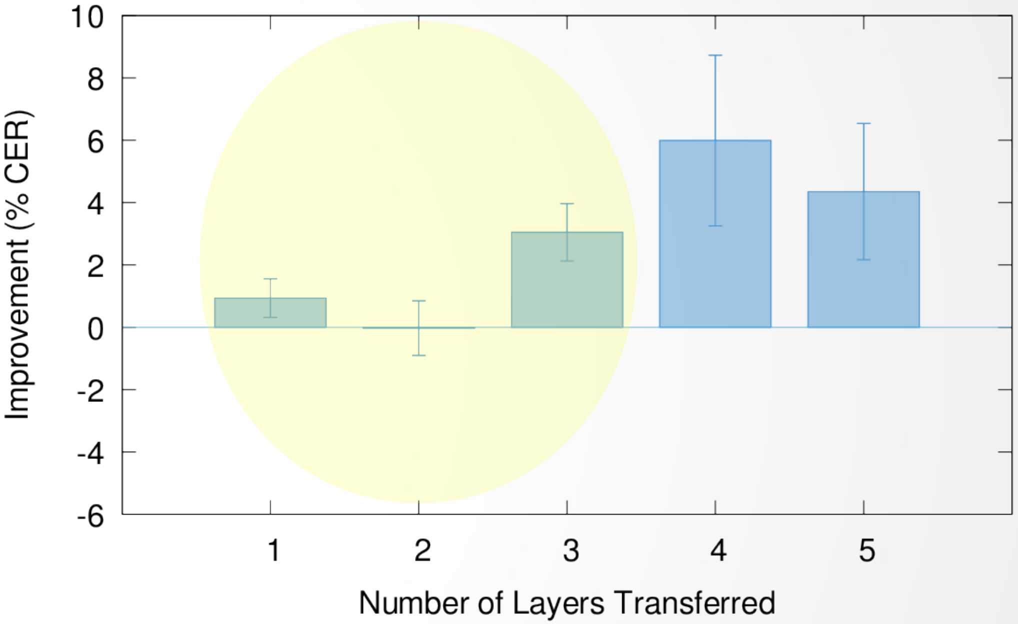
Frozen vs. Fine-Tuned





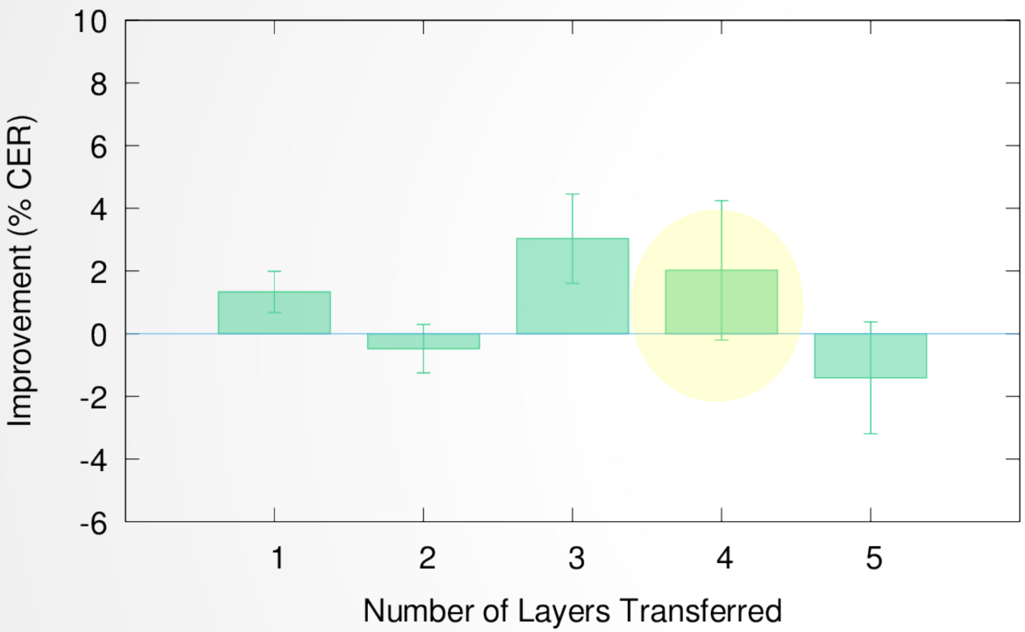
Frozen vs. Fine-Tuned

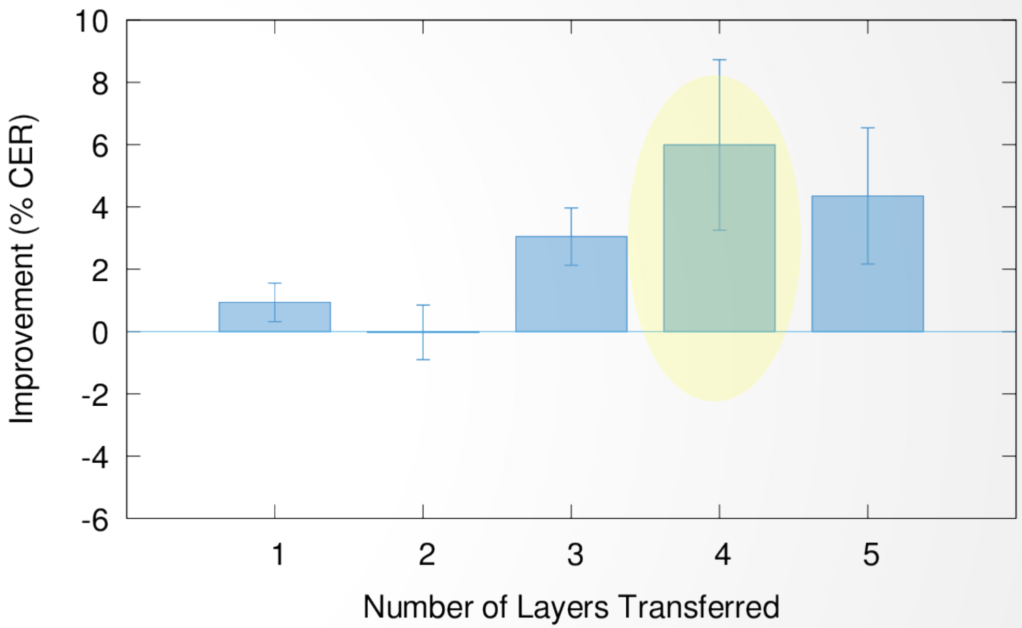




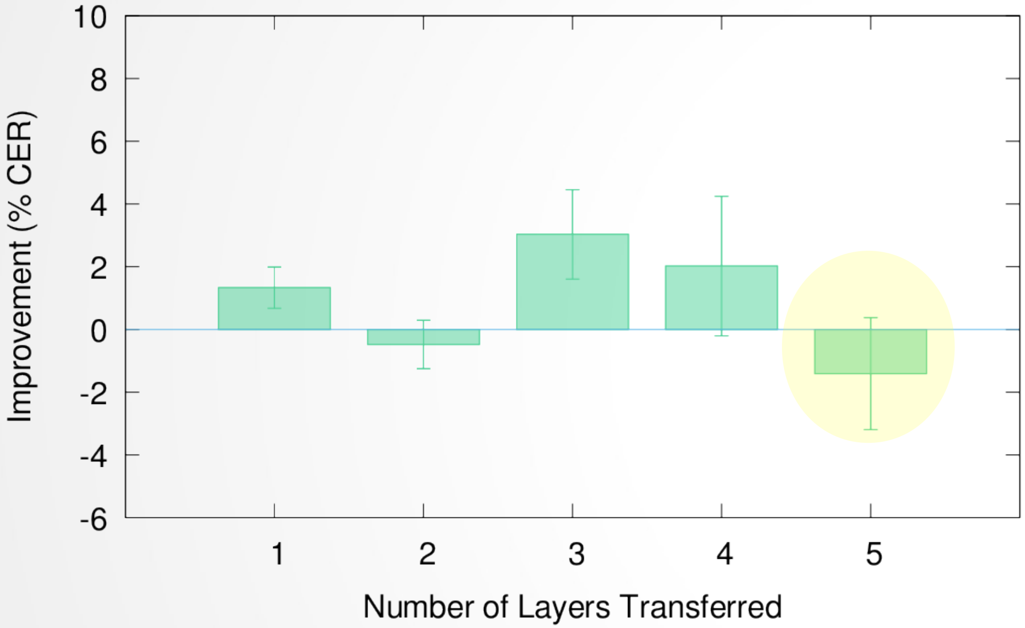
Frozen vs. Fine-Tuned

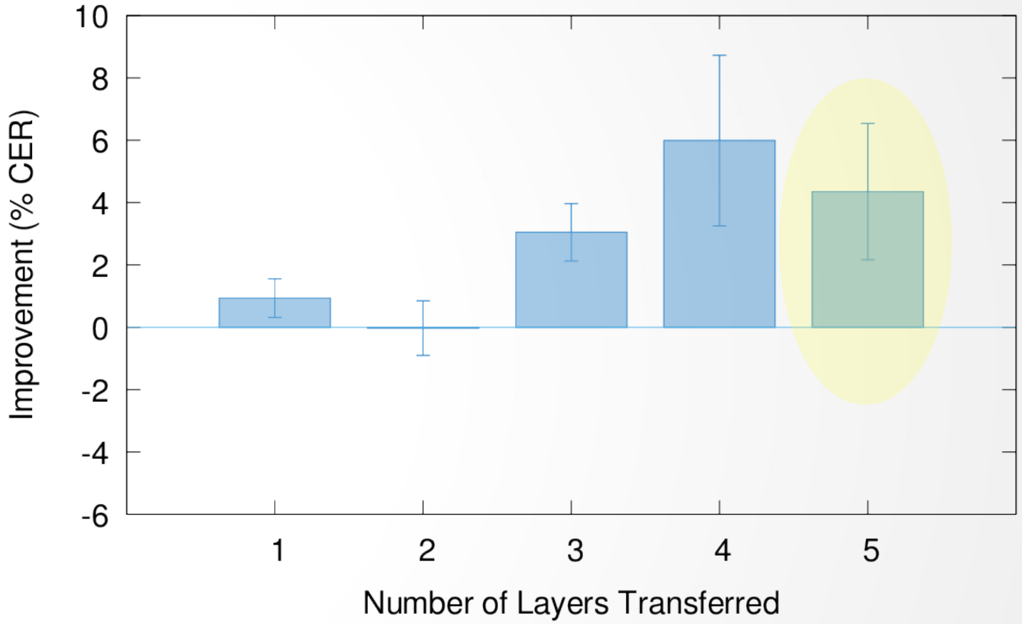
LSTM!





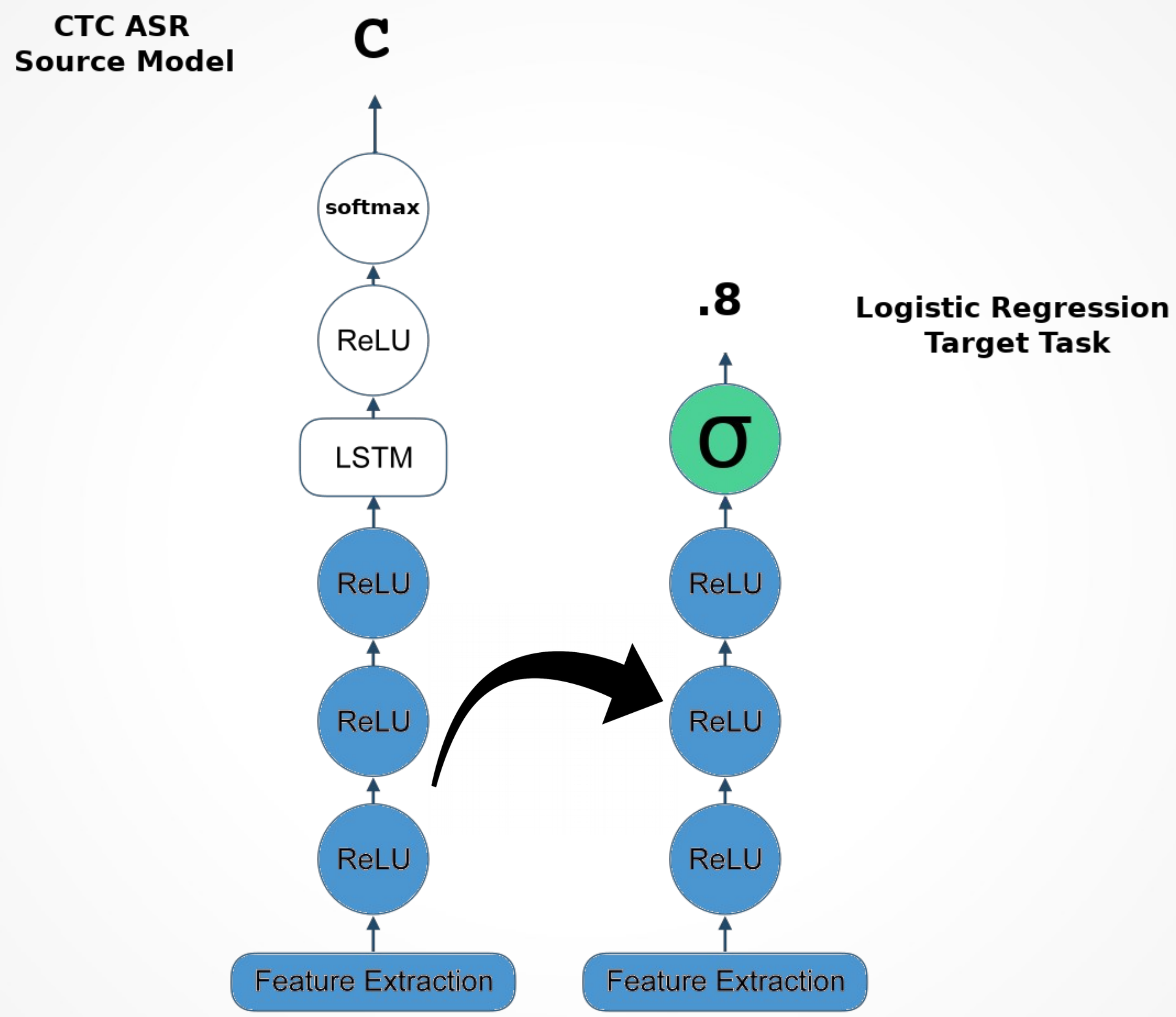
Frozen vs. Fine-Tuned



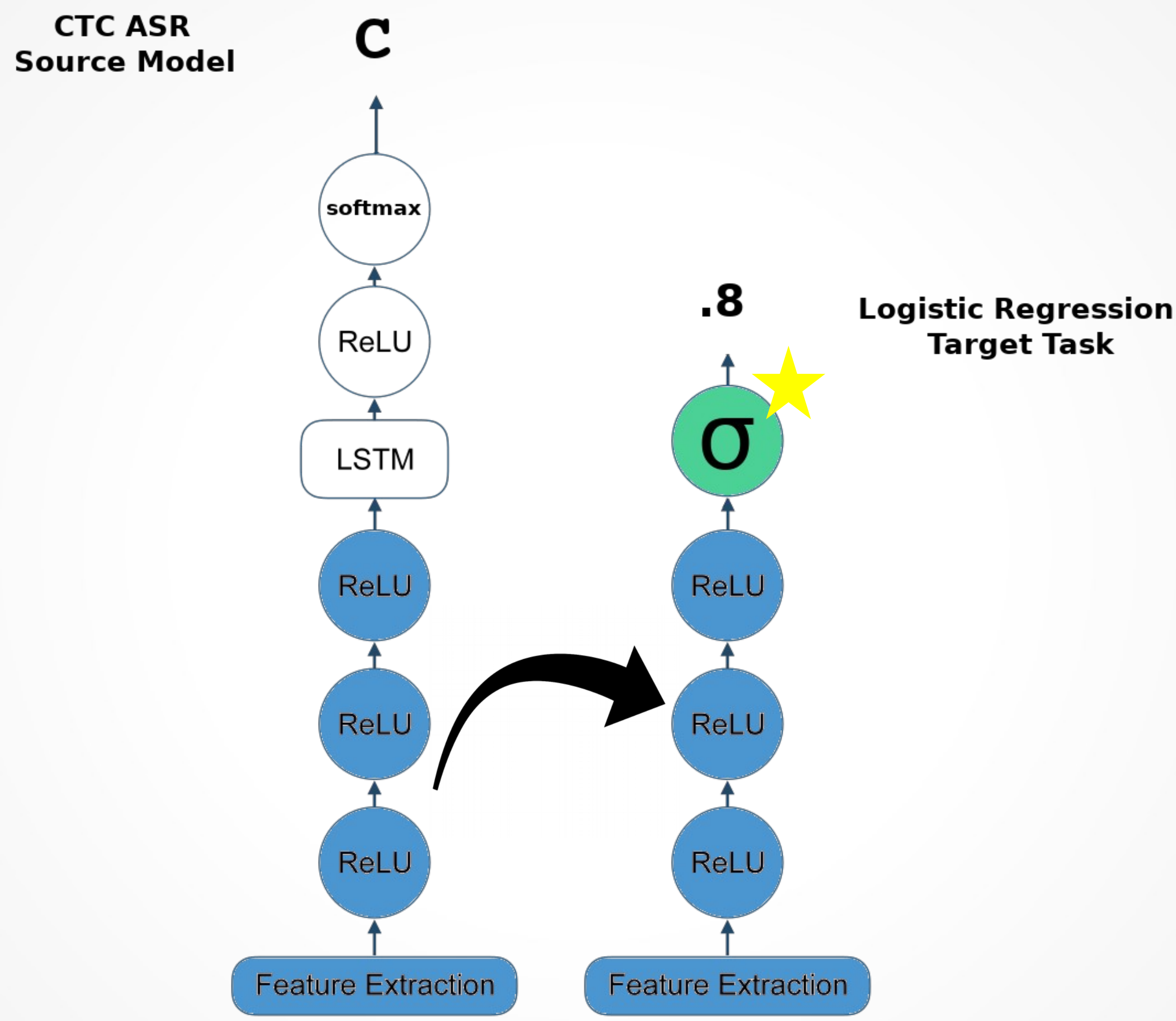


Interpretability Experiments

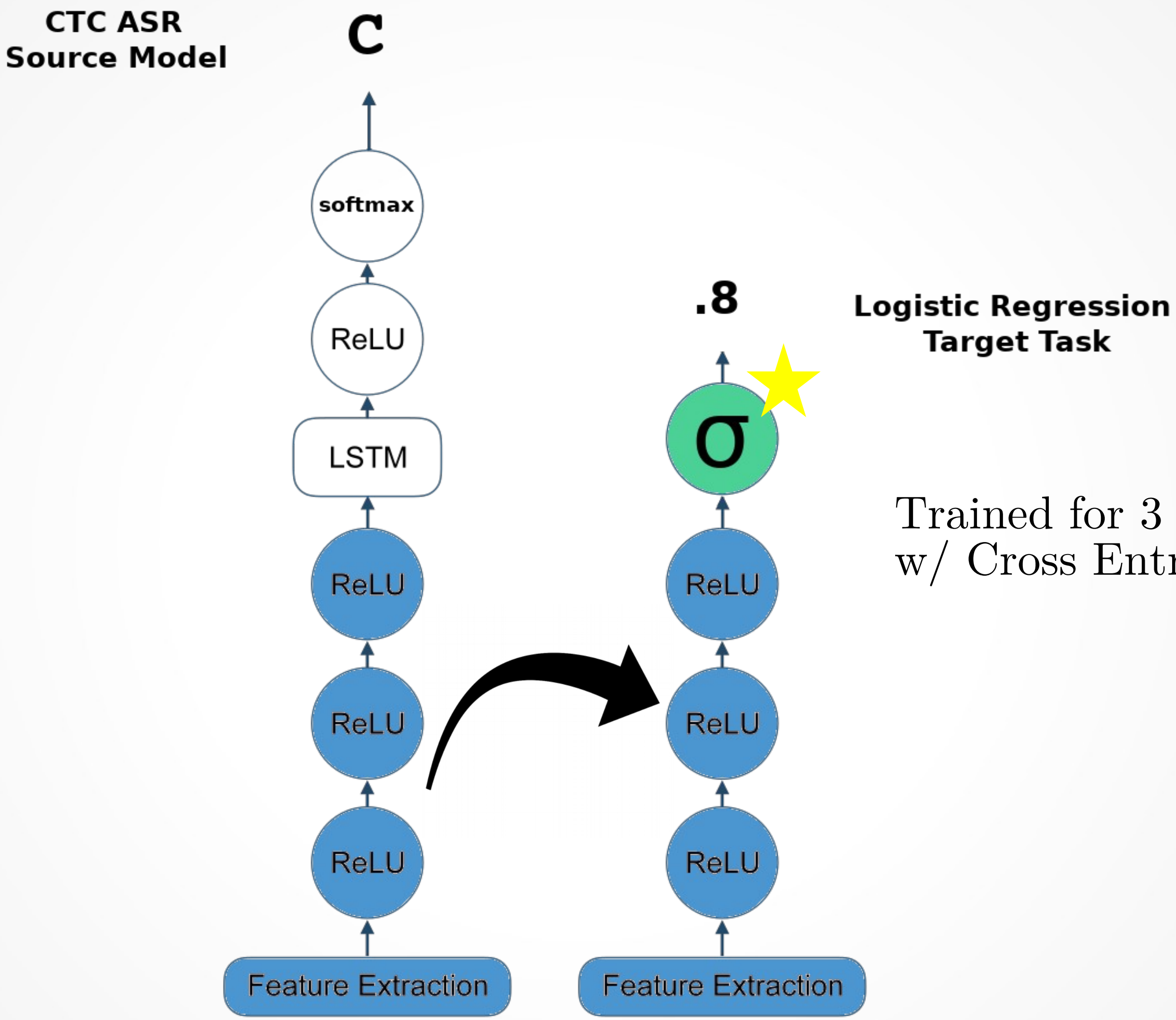
Regression on Embeddings



Regression on Embeddings



Regression on Embeddings



Trained for 3 epochs
w/ Cross Entropy Loss

Regression Results

Speech vs. Noise

- 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

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- 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 (%)

Discussion

Discussion

1) Transfer in ASR

- Fine-tuning always helps

- LSTM transfer is best, but only with fine-tuning

2) Interpretability Studies

- At the third layer, the model has learned general speech, but language-agnostic representations

Thank you for your attention!

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 A: Multi-Task

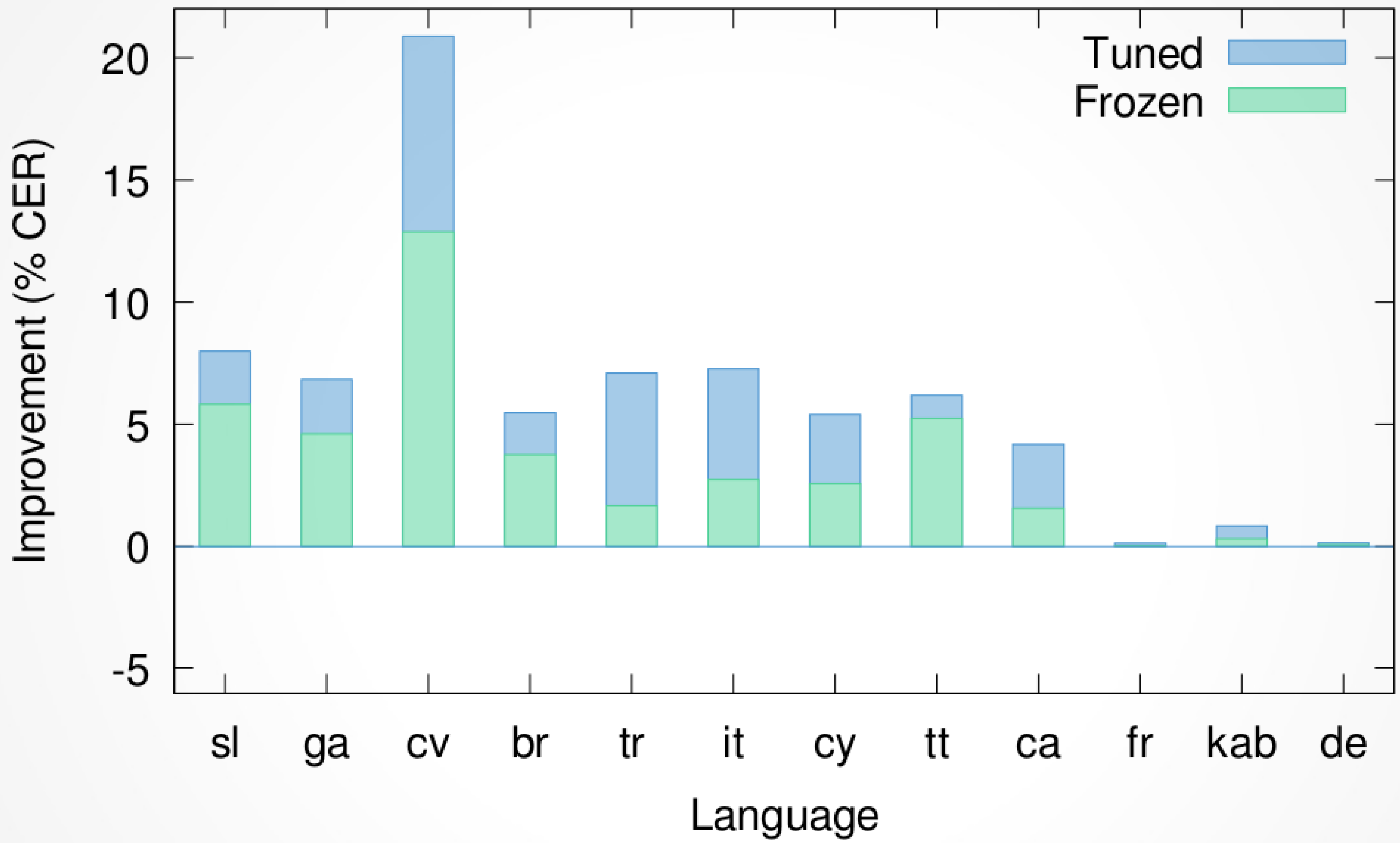
APPENDIX B: DeepSpeech

Data Details

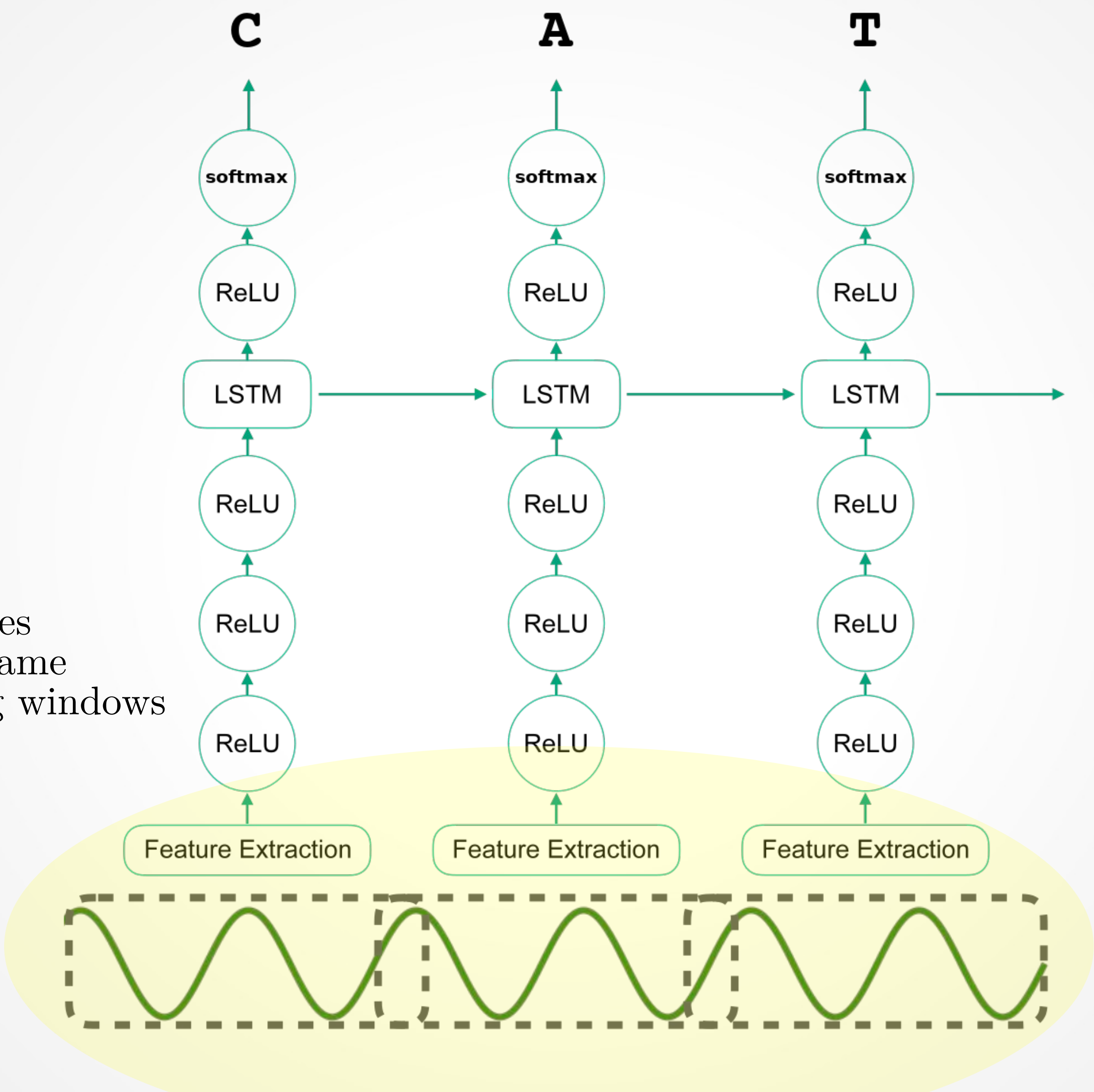
		Dataset Size					
		Audio Clips			Unique Speakers		
Language	**Code**	Dev	Test	Train	Dev	Test	Train
Slovenian	`sl`	110	213	728	1	12	3
Irish	`ga`	181	138	1001	4	12	6
Chuvash	`cv`	96	77	1023	4	12	5
Breton	`br`	163	170	1079	3	15	7
Turkish	`tr`	407	374	3771	32	89	32
Italian	`it`	627	734	5019	29	136	37
Welsh	`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



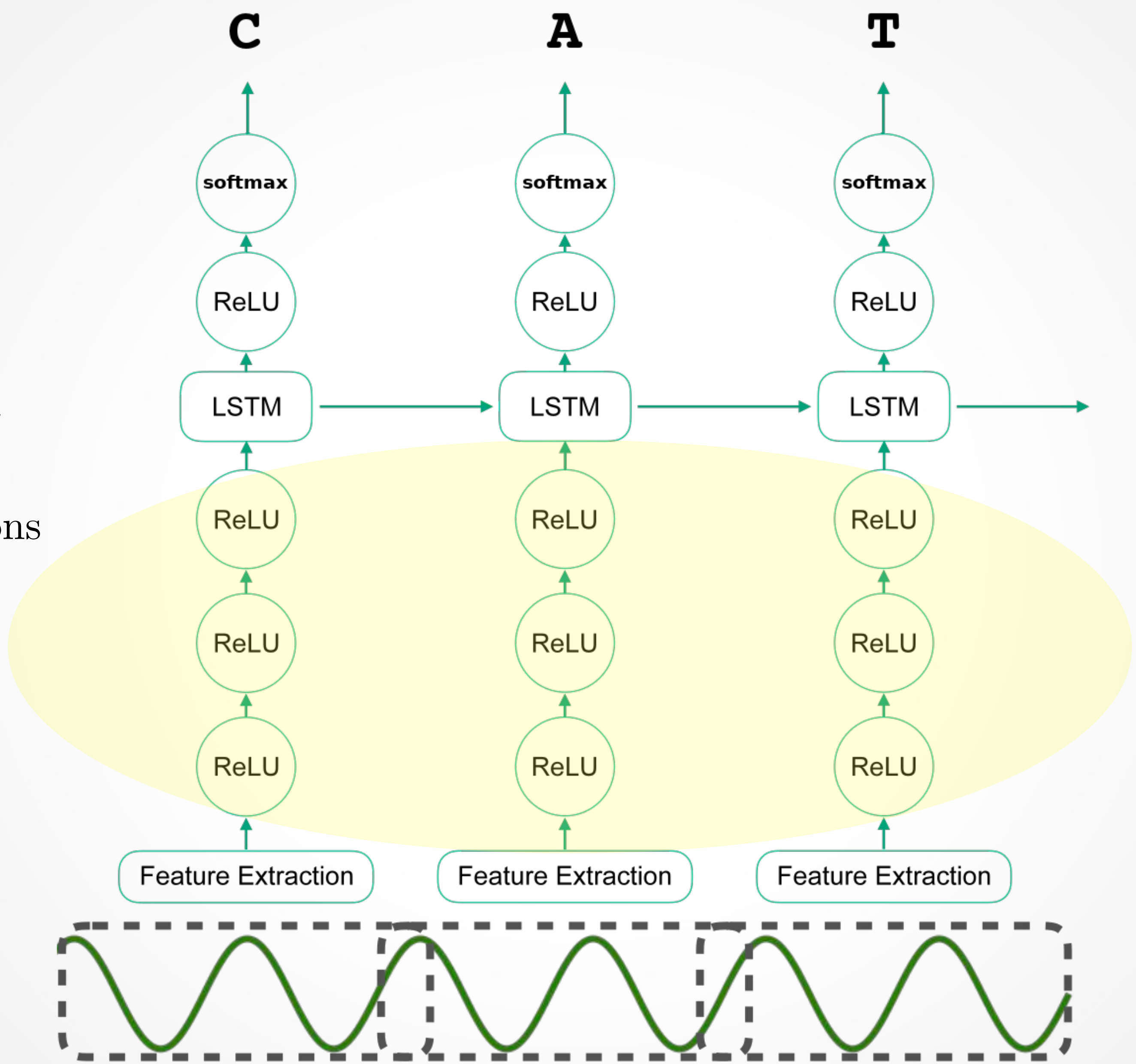
Model Architecture



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

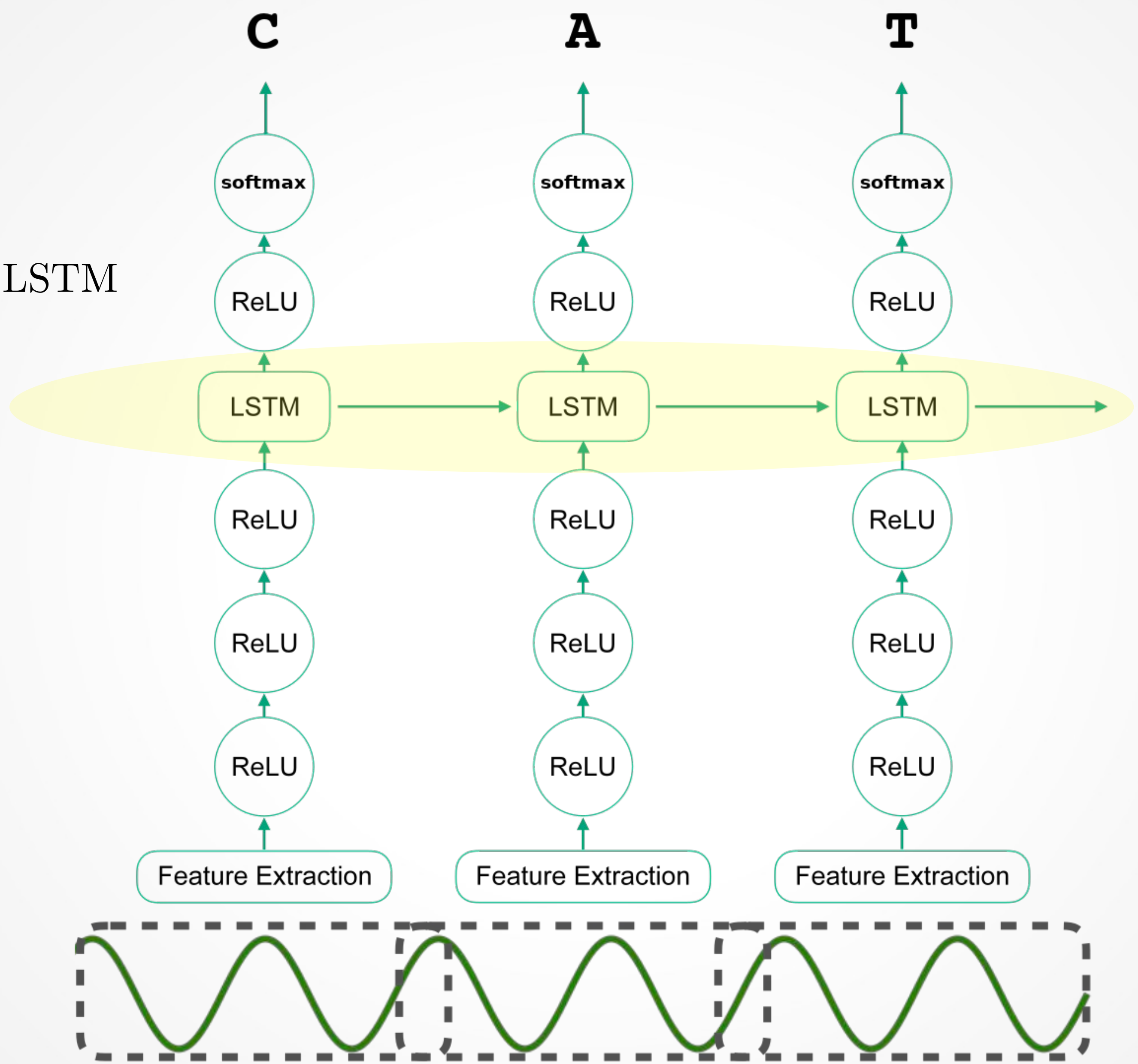
Model Architecture

Fully connected
Feed-Forward
2048 dims
ReLU activiations



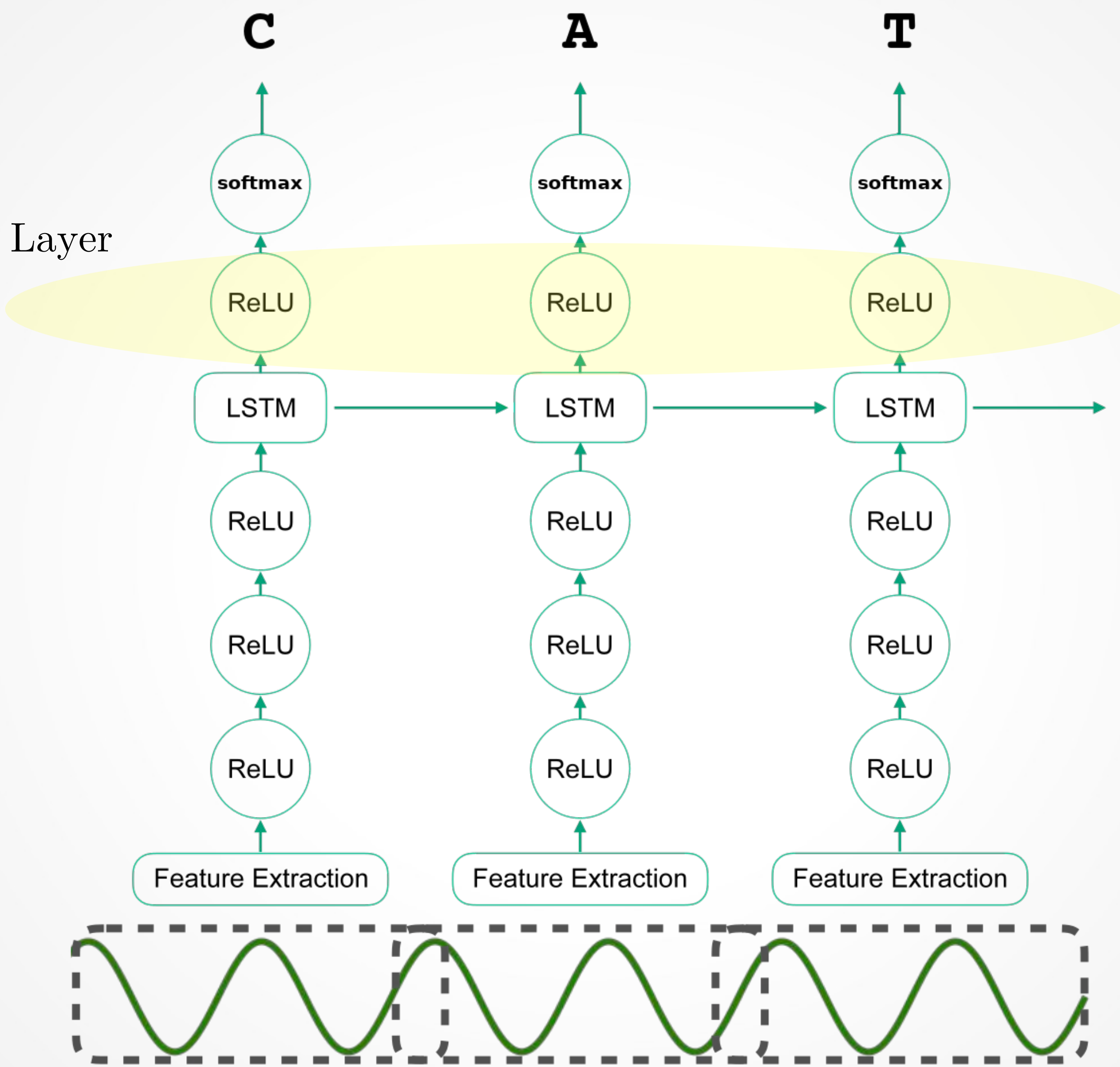
Model Architecture

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