## Role of Language Models in ASR

Al4Bharat Speech Team







## Why do we need LM?

- Speech = Acoustic + Language
  - How much of Language Characteristics is captured by Acoustic Models?
  - *Example #1*:
    - GT: आज सुनेहरा अवसर है
    - Output: आज सुनहरा अवसर है
  - *Example #2*:
    - GT: आज सुनेहरा अवसर है
    - Output: आज सुनेहरा अफसर है
  - *Example #3*:
    - GT: आज सुनेहरा अवसर है
    - Output: आज सुनेहरा अवसर हैं

Spelling Errors!

Homophones!

Inflections!

## What LM actually computes?

• Probability (Likelihood) of a sentence:

$$P(w_0...w_i) = P(w_i|w_{i-1}...w_0)P(w_{i-1}|w_{i-2}...w_0)...$$

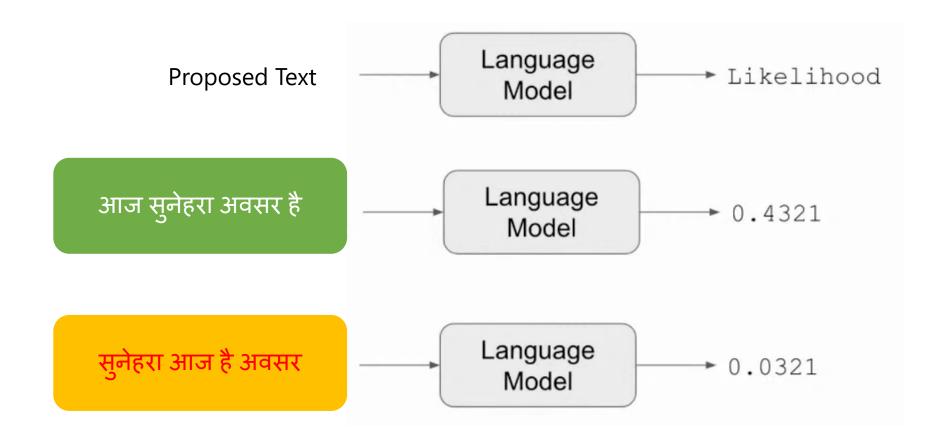
We generally limit it to N-1 previous words!

$$P(w_i|w_{i-1}...w_0) = P(w_i|w_{i-1}...w_{i-n+1})$$

- Example: Bigram Language Model
  - text = "<start> आज सुनेहरा अवसर है <end>"
  - P(text) = P(<start> | आज ) \* P( आज | सुनेहरा ) \* P(सुनेहरा | अवसर ) \* P( अवसर | है ) \* P( है | <end>)

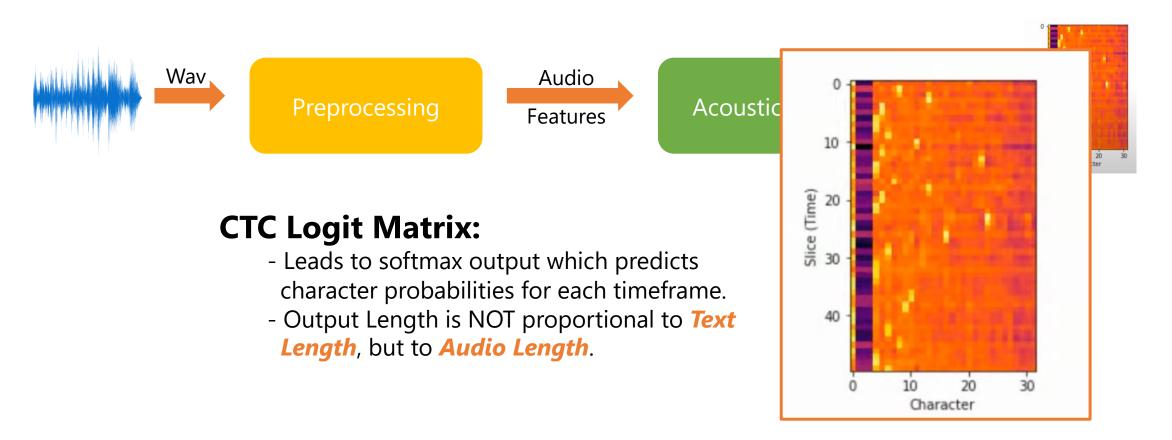
N-gram LM!

## What LM actually computes?



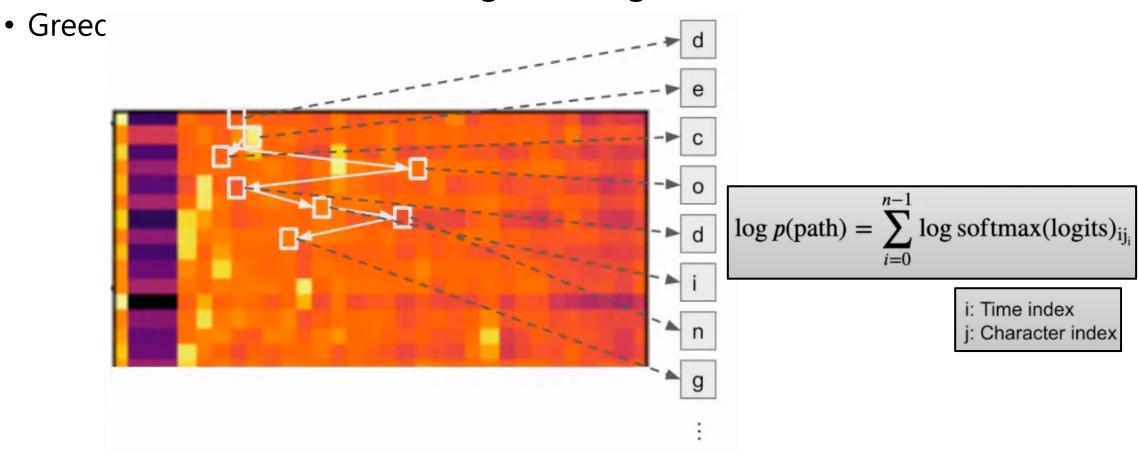
### Where do we fit LM?

Typical ASR pipeline:



# Logits Decoding - Concept

Decoder evaluates Paths through the logit matrix:



## Logits Decoding – with LM

Incorporate LM scores with logits while decoding

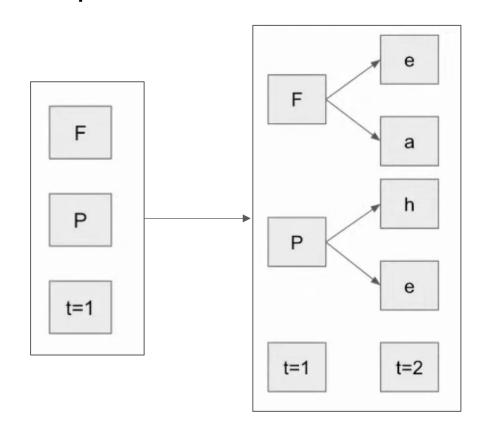
$$\log P_{\rm LM}({\rm text}) = \log P({\rm text}) + LM({\rm text})$$

- Exact/True Solution
  - Score every possible path through logit matrix with addition of LM
  - Combine scores of equivalent paths
  - Take the highest-scoring text

**Extremely Slow!** 

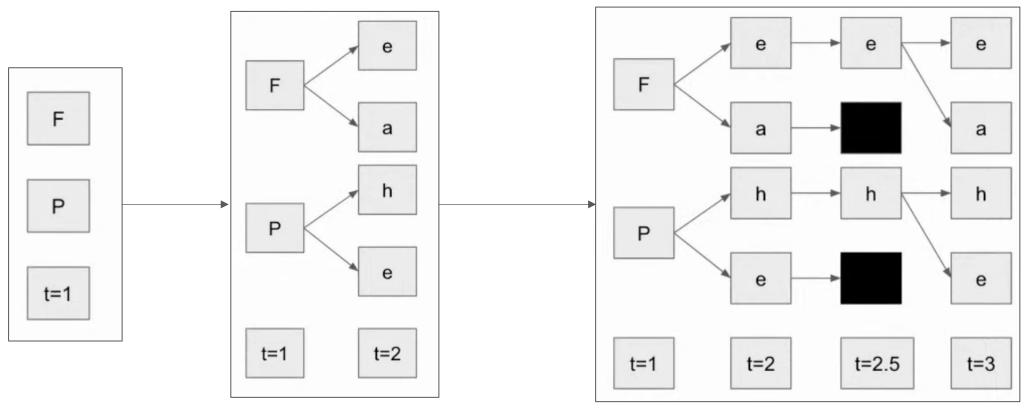
# Beam Search: Fast Approximate Solution

Step 1: Select the N best characters from the first time slice



## Beam Search: Fast Approximate Solution

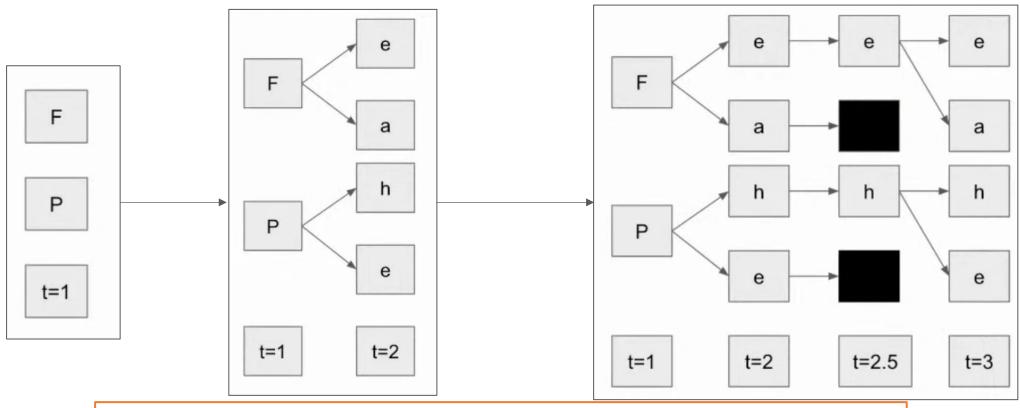
Step 2.5: Rescore text outputs with the language model.



2.5: **PRUNE** on the basis of **beam size** 

## Beam Search: Fast Approximate Solution

• Step 3: Continue by adding 3<sup>rd</sup> timestep, choosing the N best ...



If **Beam-size = 1** => Greedy Decoding; if **Beam-size = inf** => Exact Soln

### Tools of the Trade

#### **Pyctcdecode**

- Support for *Hotwords* •
- Easy to Setup & Experiment
- Direct Support for Huggingface Speech Models, NeMo Speech Models, etc.
- Comparively *Slower* because of Python Implementation
  - No support for Neural Language Models

#### Flashlight

- Supports decoding with Neural Language Model #
- Extremely Fast Decoding \*\*
- More *Configurations* Options
- Rapidly Evolving Library with limited backwards compatibility
- Official Documentation Only supports Fairseq

- Training *Kenlm* 
  - Step 1: Creating ARPA file

```
print("Creating ARPA file ...\n")
subargs = [
        os.path.join(args.kenlm_bins, "lmplz"),
        "--order",
        str(args.arpa_order),
        "--temp_prefix",
        intermediate_dir,
        "--memory",
        args.max_arpa_memory,
        "--text",
        sents_path,
        "--arpa",
        lm_path,
        "--prune",
        *args.arpa_prune.split("|"),
if args.discount_fallback:
    subargs += ["--discount_fallback"]
subprocess.check_call(subargs)
```

- Training *Kenlm* 
  - Step 2: Filtering from Lexicon

Al4Bharat, IIT Madras

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- Training *Kenlm* 
  - Step 3: Quantizing to 8 bit

```
# Quantize and produce trie binary.
print("\nBuilding lm.binary ...")
if topk is not None:
    binary_path = os.path.join(output_dir, f"topk-{topk}_lm.binary")
else:
    binary_path = os.path.join(output_dir, f"lm.binary")
subprocess.check_call(
        os.path.join(args.kenlm_bins, "build_binary"),
        "-a",
        str(args.binary_a_bits),
        "-q",
        str(args.binary_q_bits),
        "-v",
        args.binary_type,
        filtered_path,
        binary_path,
```

- Decoding with pyctcdecode
  - Build CTC Decoder

```
decoder = build_ctcdecoder(
    labels = vocab,
    kenlm_model_path = KENLM_MODEL_LOC,
    alpha=0.5, # tuned on a val set
    beta=1.0, # tuned on a val set
)
```

Decode logits from Acoustic Model

```
text = decoder.decode(logits)
```

- Decoding with pyctcdecode
  - Decoding with hotwords

```
hotwords = ["ivan"]

text = decoder.decode(

logits,

hotwords=hotwords,

hotword_weight=10.0,
)
```

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### Some Numbers from IndicWav2Vec

- Lexicon Size: 200,000
- "n" in N-grams: 6 grams
- Avg. decrease in **WER**: 28% reduction (21.6 to 15.6)

Model	gu	ta	te	gu	hi	mr	or	ta	te	bn	ne
IndicW2V	20.5	22.1	22.9	26.2	16.0	19.3	25.6	27.3	29.3	16.6	11.9
IndicW2V+LM	11.7	13.6	11.0	17.2	14.7	13.8	17.2	25.0	20.5	13.6	13.6

WER Numbers per language

## Future Scope

- Decoding with Neural Language Models
- Better integration of Language Models
  - Deep Fusion of LM
     External LM is fused directly into the ASR model by combining their hidden states, resulting in a single model with tight integration.
  - End-to-end Training with LM

    Can we pass the gradients obtained after decoding with LM?

## प्रश्नकाल?



### Thank You

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