
EmojiSense: Emoji2Text Interpreter

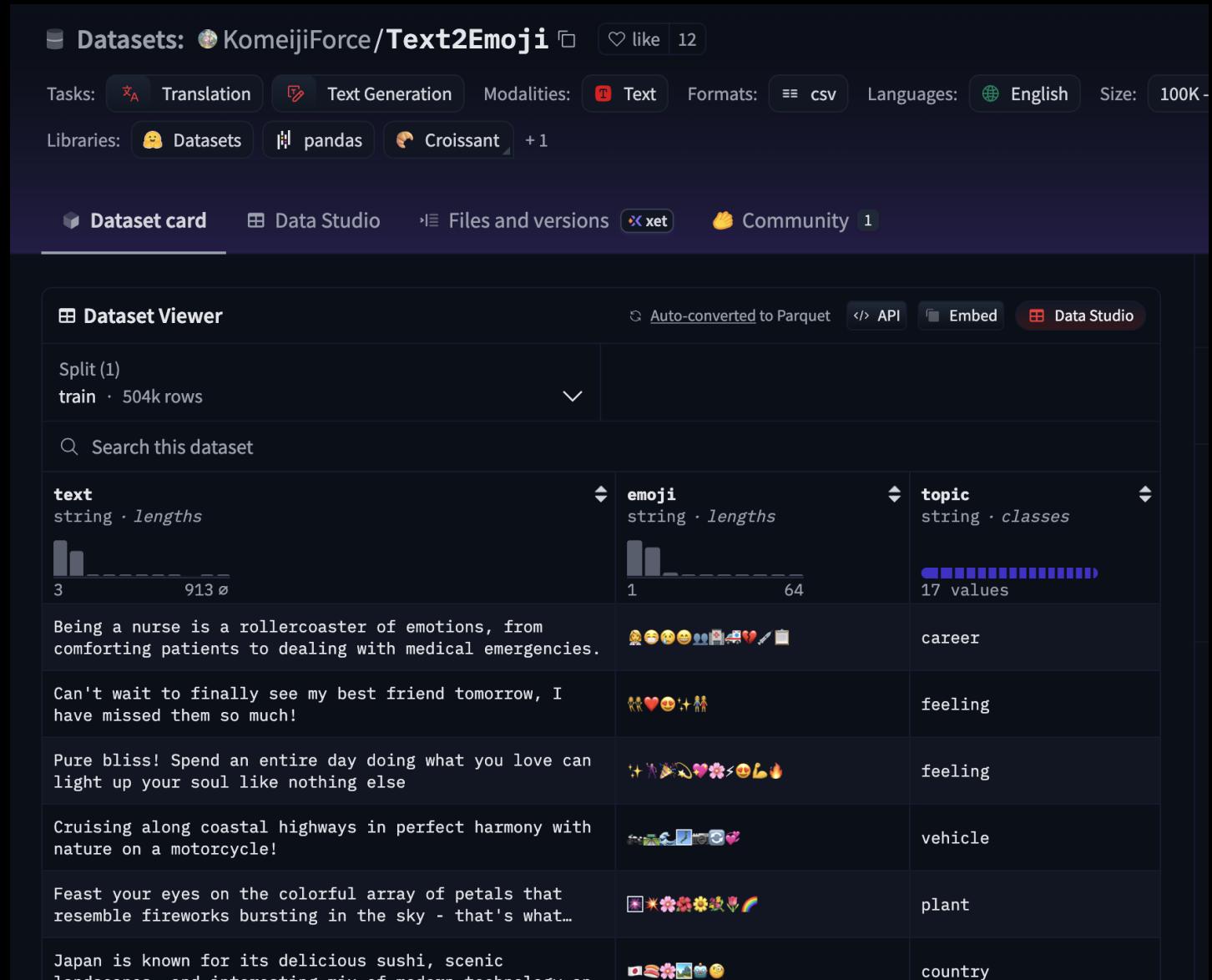


Content

- Data & Validation
- Fine-tuning Phase
- Limitation and Future Work

Where we got our data

- We use the *Text2Emoji* dataset from hugging face (Peng et al., 2023)
 - contains 504,000 rows of text to (pure) emoji data samples
 - synthetically generated using ChatGPT-3.5
(LIMITATION!)



Cross-LLM Validation

```
PROMPT = """You are an expert in interpreting emojis into natural English sentences.  
Here are some examples:
```

```
🔥🌙 → We're having a bonfire party tonight.  
 Rica 🎉 → The origami crane took forever to fold.  
 🎉🎉😊 → I caught the bouquet at the wedding.  
 ❄️🏔️🚫 → The avalanche blocked the mountain road.
```

```
Now interpret the following emoji sequence in a similar way.  
Write one fluent English sentence.
```

```
Emoji: {emoji}  
Sentence:"""
```

```
def cosine(a: str, b: str) -> float:  
    va = embedder.encode(a, convert_to_tensor=True, normalize_embeddings=True)  
    vb = embedder.encode(b, convert_to_tensor=True, normalize_embeddings=True)  
    return float(st_util.cos_sim(va, vb).item())
```

- **Validation Model:** *Mistral* (Open Source LLM)
- **Reverse-Generation Task:** Few shot prompting with Mistral to reconstruct text sequences solely from the emoji inputs
- **Semantic Comparison:** Calculated **cosine similarity** between the *original text* and the *Mistral-generated text*
- **Filtering Threshold:** Discarded samples with similarity scores < **0.6**
- **Final Outcome:** A curated, high-quality dataset of **200k samples**

Content

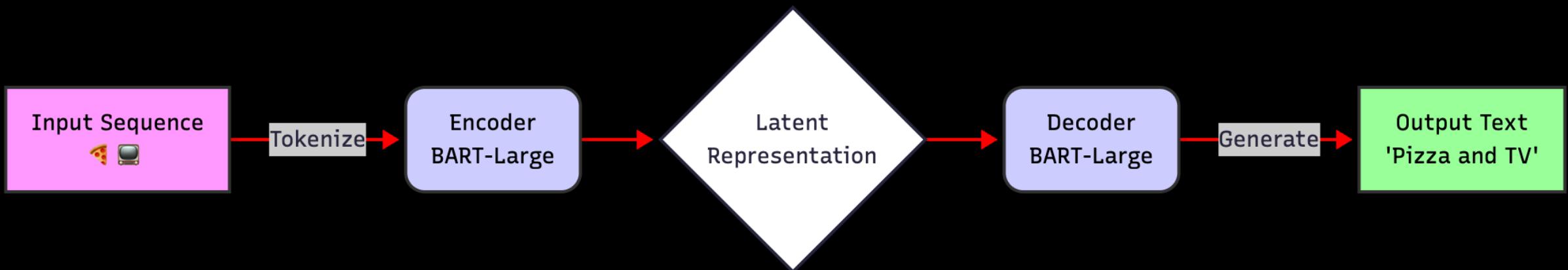
- Data & Validation
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- Limitations and Future Work



Step 1: Baseline
model

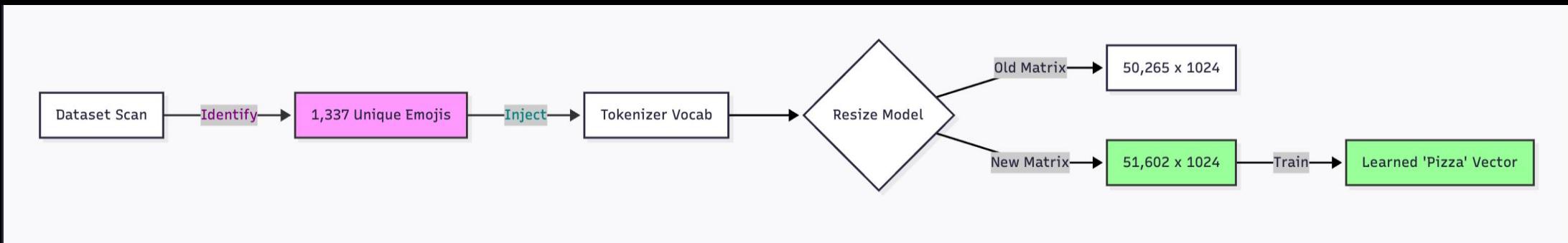
Model & Data

- Utilized **BART-Large** (FaceBook/bart-large), a pretrained Transformer encoder-decoder architecture optimized for translation tasks
- The Dataset: 100k samples randomly selected from the validated 200k dataset, split 80/10/10 for train/validation/test
- The Objective: Treat Emojis as a distinct source language and English as the target language (Emoji → English text)

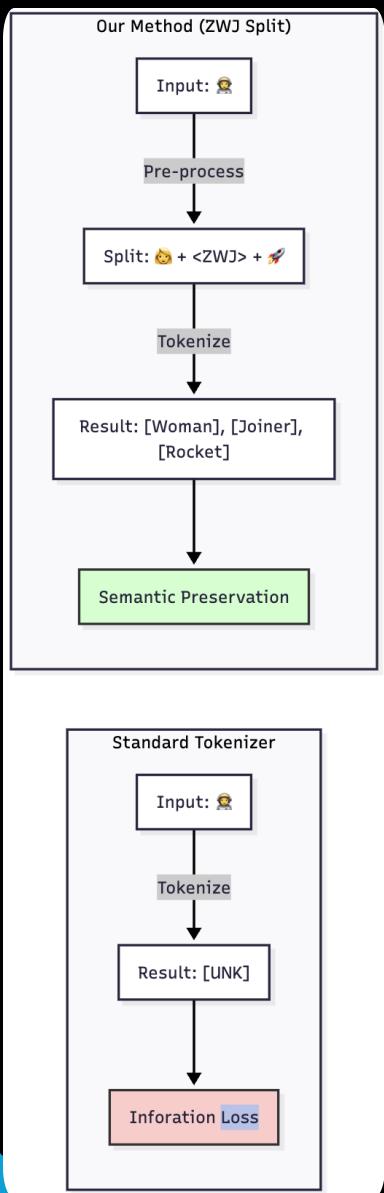


The Tokenization Problem

- **The Limitation:** Pre-trained BART models are trained on English text (Wikipedia, Books). **They have zero emojis in their vocabulary**
- **The Consequence:** Without modification, BART sees every emoji as an <unk>
 - Input: 🍕 → Model Sees: [UNK] → Output: Random guessing
- **The Fix:**
 - Scanned the entire dataset to identify **1,337 unique emojis**
 - **Manually injected** these tokens into the BART tokenizer
 - **Resized the Embedding Layer** to learn these new emojis from scratch



The ZWJ "Grammar"



- **The Problem:** Standard tokenizers treat complex emojis (e.g., 🚀) as single, unknown tokens (<unk>)
- **The Insight:** Complex emojis are compositional. They are distinct Unicode characters glued together by a **Zero Width Joiner (ZWJ)**
- **The Solution:** Implemented a custom pre-processing function that explicitly splits emojis by the \u200d (ZWJ) character and use it during tokenization

Model Outputs and Human Evaluation

Input: 🍕 📺 🎵

Pred : Pizza is the perfect combination of cheesy goodness and deliciousness.

Input: 😢 🏥 💊

Prediction: I am passionate about pursuing a fulfilling career in the field of medicine.

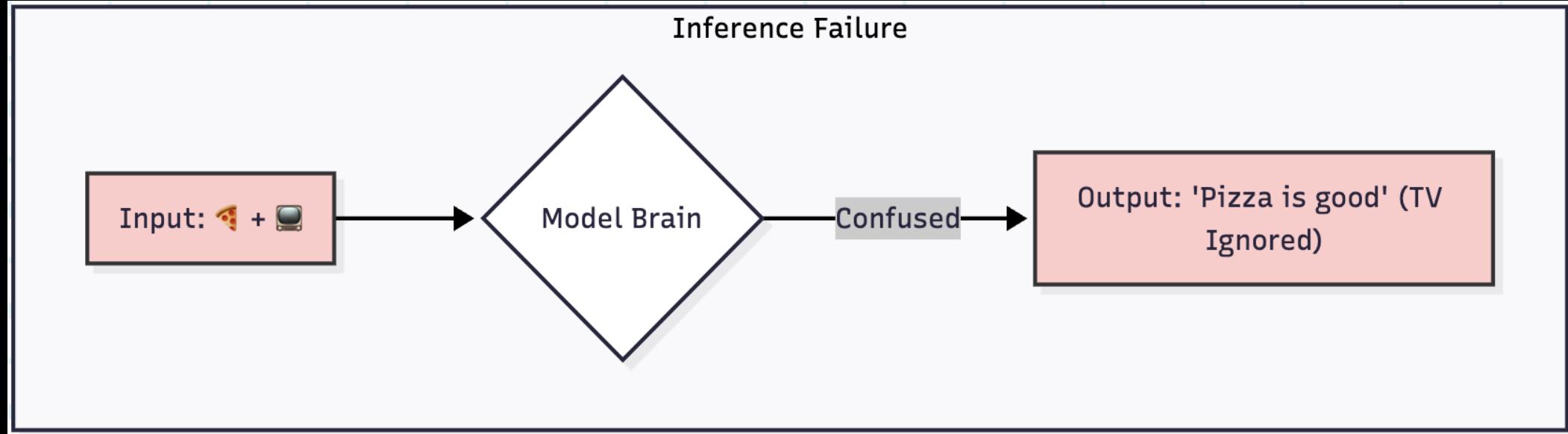
Input: 🌱 🌿 💚

Pred : The Venus Flytrap is a carnivorous plant that captures insects with its trap-like leaves.

It's not that good.... Why?

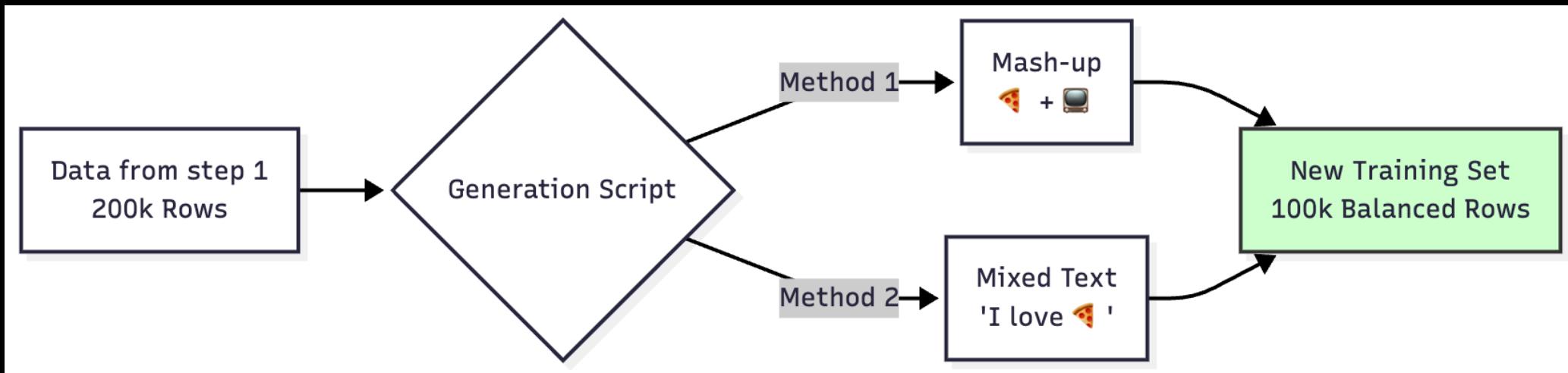


Step 2: Multi-Domain
& Multi-Modal Model



The "Isolated Domains" Problem

- **The Problem:** The training data (based on Emoji2Text) were "disjoint"
 - The dataset contained 19 distinct domains (Food, Activities, Weather)
 - The model never saw a "Food" emoji next to an "Activity" emoji
- Example: When faced with 🍕 📺 (Pizza + TV), the model picked the strongest signal ("Pizza") and completely ignored the other ("TV"), failing to synthesize the story



The Fix: Synthetic Data Augmentation

- **Method A: "The Mash-up" (Context Mixing)**
 - Randomly concatenated examples from different domains
- **Method B: "Mixed Modality" (Code-Switching)**
 - Randomly injected emojis into standard English sentences
 - *Example:* "I love pizza" → Input: "I love 🍕"
- **Scale:** Generated a synthetic balanced dataset of **100,000** examples (70k Original + 15k Mashup + 15k Mixed Modality)

Step 2 Results and Human Evaluation

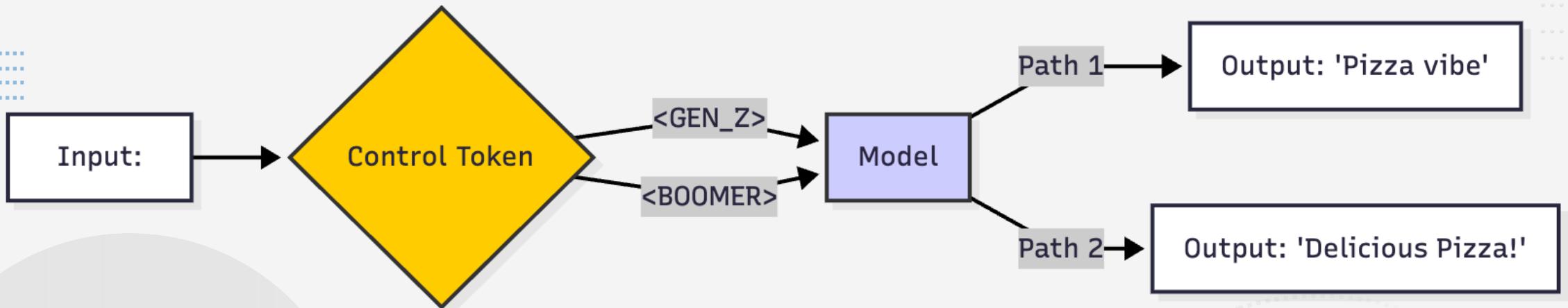
Trained a fresh BART-Large model on the new dataset for **10 epochs** using **A100 GPUs** to ensure deep convergence

Conclusion: The model is now **Context-Aware** and capable of **Multi-Modal** understanding

Input Type	Input Sequence	Baseline Output	Model 2 Output
Mash-up	 	"Pizza is delicious."	"Pizza and Netflix!"
Mixed Text	My  broke.	"My."	"My car broke."



Step 3: The Age Parameter



translation isn't just about meaning; it's about *tone*!

The Challenge: "Standard" English is often too robotic for emojis. A teenager (💀) and a grandparent (💀) use the same symbol to mean completely different things ("Laughter" vs. "Death")

The Solution: Introduced **Control Tokens** to append to the input and condition the model's generation

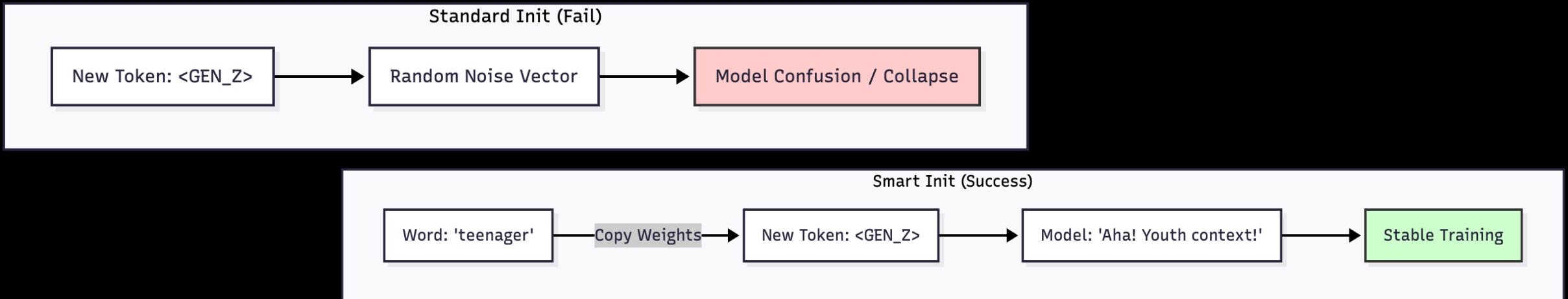
- <STD>: Standard/Neutral translation
- <GEN_Z>: Slang, lowercase, hyperbolic tone
- <BOOMER>: Formal, sincere, correct grammar & punctuation

```
1 emoji,text,topic
2 <GEN_Z> ⚾⚾⚾, "those baseball players just totally boss on the field, throwing curveballs, smacking homers, and sliding like they
3 <GEN_Z> ☀️🌴, "Time to chill by the ocean and bask in the rays all day, yeah",gen_z
4 "<GEN_Z> Nothing beats a warm blanket, a cozy movie, and some fluffy 🛌 on a chilly fall afternoon.", "nothing gonna beat a warm blan
5 <GEN_Z> 🏖️☀️, "gotta hit the sandy shores in a flashy buggy, chillin' under the sun, feelin' the ocean vibes.",gen_z
6 "<GEN_Z> 🏀 requires skillful running, sprinting, and collective strategic movements.", "basketball's all about slayin' on the court,
7 <GEN_Z> 🔨💡🔨🔨, the hammer's just a fancy pickhandle for when ur trying to DIY stuff.,gen_z
8 <GEN_Z> 🥑🥑🍞, "kick off your morning with some avo toast chucked on there, crowned with a egg that's poached like it's got a PhD
9 <GEN_Z> 🎅❄️🎄🎅, "hmmmm, merry christmas from the cute penguin bunch, they're so adorable with their fluffy black & white suits
10 <GEN_Z> I can hear the sound of rain hitting my 📈 and feel the cooling breeze rushing inside., "hearin rain hitin my window, and fee
11 <GEN_Z> 🌧️🌧️☂️☂️, "pff, it's raining cats and dogs out there, dude. don't forget your trusty umbrella before you bail from your pad
12 <GEN_Z> The grand 🏰 was fit for royalty with its soaring towers and intricate design., "That mansion was like, totally 🏰 worthy wit
13 <GEN_Z> 🧘🧘‍♀️🧘‍♂️🧘, "just chilled out with some yoga, totally zen-like.",gen_z
14 <GEN_Z> 🌮🔥🌮, "got the hankerin' for some tasty tacos to add some flavor to my day, fam.",gen_z
15 <GEN_Z> 😬🤔🧐🤔🧐🤔🧐🤔🧐, "today was legit a doozy, feels like my brain's gonna explode. and those ballers are tryna crush it,
16 <GEN_Z> ⚽⚽⚽⚽⚽, "f the thrill of watching football, the sound of your kicks on the grass, and the crowd going nuts - no
17 <GEN_Z> Using a 🚲 as a means of commuting reduces carbon emissions., "cycling to work is totally eco-chillin', cuts the ghastly carb
18 <GEN_Z> 🏙🏛️🏛️🏛️, "this country's buildings and old stuff is lit and gnarly, pulling in a ton of wanderers.",gen_z
19 <GEN_Z> 🎉🎉🎊🎊🎊, "ya know, gettin' down with the role of an event planner, makin' peeps happy and turnin' daydreams into real
20 <GEN_Z> 🎧🎧🎧, "lol bought a new soundbar today, totally leveling up my audio game.",gen_z
```

The "Teacher-Student" Loop

- **Synthetic Data Generation:** We used a "Teacher" LLM (*Microsoft Phi-3*) to generate training data for our "Student" model (BART)
- **Prompt Engineering:** Rewrote Step 2 sentences into specific personas
 - "You are a Gen Z translator. Rewrite the input sentence using slang, lowercase, and irony."
- **Dataset Composition:** Created 40k stylistic examples (20k Gen Z, 20k Boomer) mixed with 60k Standard examples

The Collapse & The Fix



- **The Failure:** Initially, training failed. The model "collapsed," ignoring inputs and outputting repetitive garbage ("The The The...")
- **The Root Cause:** The new control tokens (<GEN_Z>) were initialized as **random noise**. This "shocked" the pre-trained model, destroying its weights during early training
- **The Fix: Smart Initialization**
 - We manually copied the embedding weights from semantically similar English words to initialize the new tokens
 - <GEN_Z> → initialized from "**teenager**"
 - <BOOMER> → initialized from "**formal**"
- **Result:** The model started training with a "hint" about what the tokens meant, leading to stable convergence

FINAL RESULTS

- **Qualitative Success:** The model successfully nuances meaning based on the persona
 - *Context Awareness:* It interprets 🚗 as "whip/car" for Gen Z and "automobile" for Boomers
 - *Tone Shift:* It changes punctuation and capitalization patterns dynamically
- **Final Deliverable:** A functional, interactive web demo running the live model

```
🤖 EMOJI-LM AGE PARAMETER EVALUATION
=====
Input: 🍕📺 (Pizza + TV)
STD : Pizza night with friends is always a good idea!
GEN_Z : i'm totally vibin' with some pizza and binge-watching my fave show.
BOOMER : Nothing compares to the sheer delight of savoring a delectable slice of pizza on a Friday evening!
```



Content

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- Fine-tuning face
- Limitations and Future Work

Limitation & Constraints

- We can't promise that we have **all** the emojis in our model's vocab...
 - Results in Out-of-Vocabulary (OOV) errors or unpredictable inference on rare emojis
- The "Teacher-Student" training loop relies entirely on the Teacher LLM's capabilities...
 - If the Teacher LLM hallucinates or exhibits bias, these flaws are distilled into our model



Possible next step

Scaling & Generalization

- Expand model capacity by increasing the training corpus size
- Extend training epochs to improve convergence and reducing loss

Further Validation

- Develop a secondary validation layer for the "Teacher-Student" pipeline (Step 3)
- **Goal:** Systematically filter low-quality or hallucinated outputs from the Teacher model to reduce noise

References

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