AMAZON VIDEO GAME REVIEWS

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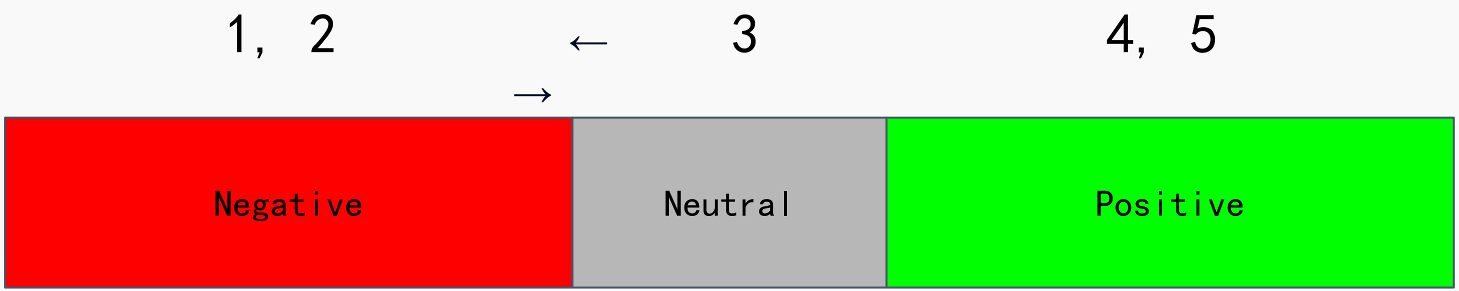
Background and Purpose

Background

- People's perspective and tastes are different
- Reviews serves as important feedback
- The grey area



Purpose

Objective: Be able to capture the personality of a user to predict their possible next review

- **Step 1:** Sentiment Analysis ✓
- **Step 2:** Recommender System …
- **Step 3:** Sentiment Analysis + Decoder
- **Step 4:** Merge all steps

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PART

Data Description and Preparation

Data Description and Preparation

- **Data Resource:**
  Amazon review dataset released in 2014 (videogames category 2018)

- **Data Size:**
  The original dataset contains **2.5M** reviews, but we use a subsample of **497k** reviews

- **Columns:**
  Rating, User ID, Text review

Data Loading

Data Cleaning

➔ Drop empty columns

➔ Delete the punctuations

➔ Relable the rating

Data tokenized and standarlization

➔ Create and tokenize a vocabulary pool

➔ Tokenize each review text

➔ Standardize tokenized review

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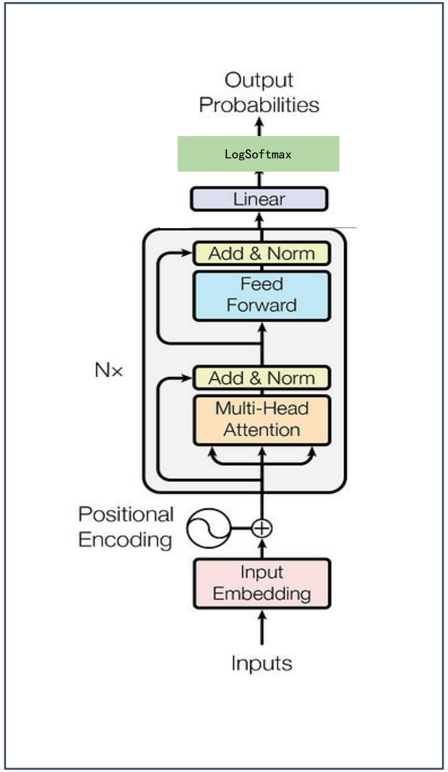
PART

Sentiment Analysis

Modeling

- Long short-term memory (LSTM) network
  - Embeddings: 182031, 400 dim
  - LSTM Layer: 3 layers, 0.5 Dropout
  - Dropout: 0.3
  - Linear Layer (Fully Connected)
  - ELU Activation Layer
  - Criterion: CrossEntropyLoss

- Transformer-Encoder
  - Positional Embeddings: 512, 1024 dim
  - Multi-Head Attention Layer: 2, 4 attention heads
  - Normalization Layer 1
  - Feed-Forward: Two linear layers - ReLU
  - Normalization Layer 2
  - Dropout: 0.2
  - Linear Layer - LogSoftmax
  - Criterion: NLLLoss



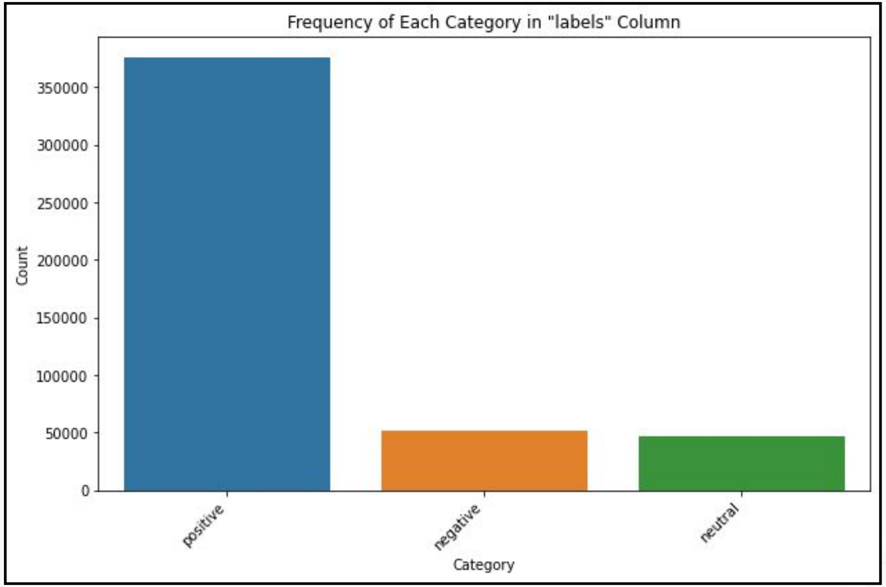
Source: Attention Is All You Need

Training and Evaluation

- Data Splitting:
  - Training: 80%
  - Validation: 10%
  - Testing: 10%

- Internal Benchmark Model (50k):
  - Transformer-Encoder
  - Embedding Dimension: 512
  - Attention Heads: 2
  - Learning Rate: 0.01
  - L2: 0.001
  - % Test Accuaracy: 79.4%

- External Benchmark Model:
  - Sentimen Analysis of Emotions
  - Number of Classes: 6
  - % Test Accuaracy: 89%



Training and Evaluation

- 100k training subsample (1+ hour)

Epochs	Embedding Dim.	Attention Heads	Learning Rate	L2	% Test Acc.
10	512	2	0.01	0.001	79.4%
10	512	2	0.001	0.0001	81.1%
8	512	2	0.001	0.00001	78.7%
8	512	2	0.03	0.0001	78.3%
6	1024	4	0.001	0.0001	80.5%
6	1024	2	0.001	0.0001	79.6%
6	512	2	0.003	0.0001	82.3%

Training and Evaluation

- 470k training sample (2+ hours)

- Best hyperparameter of other trainings:
  - Epochs: 6
  - Embedding dimension: 512
  - Attention Heads: 2
  - Learning rate: 0.001
  - L2: 0.0001

- % Test Accuaracy: 85.3%

- Why so many “positive”?

Confusion Matrix: Actual vs Predicted

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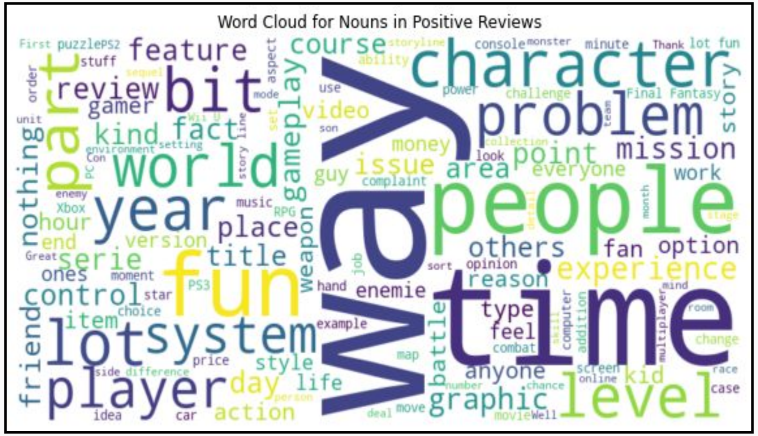
PART

Keywords Identification

Word Clouds

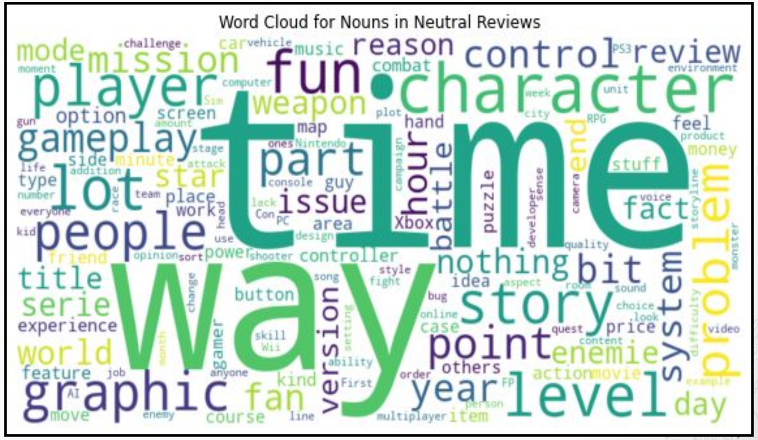
Common nouns across all sentiments include

'time', **'people'**, **'character'**, and **'problem'**.



Word Cloud for Nouns in Positive Reviews

Word Cloud for Nouns in Negative Reviews



Word Cloud for Nouns in Neutral Reviews

Keywords Identification

We choose Top 1 (**'B00JK00S0S'~ID),** a product with a leading overall rating and a substantial reviewer base, to analysis its success

TF-IDF Vectorization

Quantify the importance of the words within the positive reviews relative to their frequency.

- **Engagement Factors**: 'world', 'level', 'challenge'
- **Emotional Resonance**: 'emotions', 'feel', 'experience'
- **Game Mechanics**: 'ammo', 'difficulty', 'horror', 'stealth'
- **Distinctive Elements**:'circumference'(feature), 'joel' (a character)

Latent Dirichlet Allocation (LDA)

Uncover latent topics by applying an unsupervised learning approach to delineate thematic structures within the reviews.

- Topic 1: **Narrative and gameplay quality**
- Topic 2: **Extrinsic aspects of the gaming experience**
- Topic 3: **Emotional depth and immersion**
- Topic 4: **Technical execution**
- Topic 5: **Social component**

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PART

Deployment

Deployment

Business Application:

- **Sentiment Analysis**
  - Capture the real sentiment from the neutral reviews

- **Sentiment Analysis + Decoder + Recommendation System**
  - Capture the personality of the users and offer a automatic review
  - Capture information to recommend items that lead to the user make a review
  - **Ethical dilemma:** wrong use of data (e.g. Identity thief, fake reviews)

- **Keywords Identification**
  - Offer the analysis and feedback as a service to game developers or any other category of products.

THANKS