Text Sentiment Analysis of Douban Film Short Comments Based on BERT-CNN-BiLSTM-Att Model

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Introduction & Motivation

- Explosive growth of user-generated short texts
- Importance in e-commerce, social media, and film industry
- Challenges: high ambiguity, brevity, noise
- Need for advanced models integrating semantic understanding

Why BERT? Its Strengths

- Bidirectional transformer architecture
- Pre-trained on massive corpora
- Captures deep bidirectional context
- State-of-the-art for many NLP tasks
- Fine-tuning capability

Data Collection

- Data source: Douban movie reviews
- Web scraping with Scrapy
- Data size: ~400,000 reviews
- Text preprocessing:
- Sentiment labeling (positive/negative)
- Removing noise (long comments, English-only, emoticons)
- Uncommon characters removal

Data Preparation & Training Strategy

- Data split: 80% training, 10% validation, 10% testing
- Handling class imbalance
- Tokenization with BERT tokenizer
- Use of dropout and regularization
- Training details:
- Loss function: cross-entropy
- Optimizer: Adam
- Learning rate schedule

Proposed Hybrid Model Architecture

- Step 1: BERT for feature extraction
- Step 2: CNN for local features
- Step 3: BiLSTM for global contextual features
- Step 4: Attention mechanism to highlight key information
- Final: Sentiment classification

Model—BERT Component

- Pre-trained BERT embeddings
- Fine-tuning on Douban dataset
- Dynamic word vectors: context-aware
- Handling polysemy and ambiguity

Model—CNN for Local Features

- Convolutional layers with varying filter sizes
- Extraction of n-gram features
- Max pooling for dominant feature detection
- Capturing local syntactic cues

Model—BiLSTM for Global Context

- Bidirectional processing
- Capturing sequence dependencies
- Learning long-term semantic relations
- Complementing CNN features

Attention Mechanism

- Focuses on key words/phrases
- Highlights sentiment-relevant features
- Enhances interpretability
- Integrated with CNN and BiLSTM outputs

Fully Connected and Output Layers

- The fused and adjusted features are flattened and passed
- Incorporates a Dropout mechanism
- Ends with a SoftMax layer

Performance Comparison of Models

- Proposed Model: BERT-CNN-BiLSTM-Att
- Compared with: Word2Vec-BiLSTM, Word2Vec-CNN, Word2Vec-CNN-BiLSTM-Att, BERT, BERT-CNN, BERT-BiLSTM
- Key Result: Highest accuracy among all models
- Accuracy Values:
- BERT-CNN-BiLSTM-Att: 90.85%
- BERT: 88.22%
- Word2Vec-BiLSTM: 86.56%