Week 2: Understanding Emotions in Text

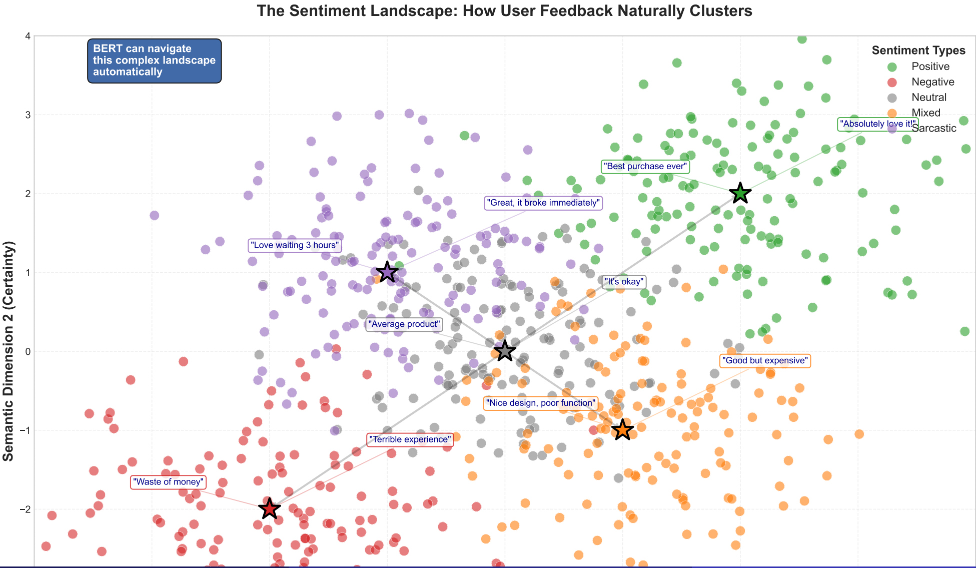
BERT + Empathize = What Users Really Mean

ML/AI/GenAI for Design Thinking

BSc Course - 12 Week Program

2024

The Sentiment Landscape



The Problem: Hidden Emotions in Text

What users write:

- "Great product... if you like disappointment"
- "Not bad at all"
- "Fine."
- "Can't complain"

What they actually mean:

- Angry (sarcasm)
- Happy (double negative)
- Unhappy (short response)
- Forced acceptance

Design blind spot:

- Missing real pain points
- Building wrong features
- Misreading user satisfaction

Design opportunity:

- Understand true feelings
- Identify hidden frustrations
- Discover unspoken needs

For Design: Words alone miss 45% of user emotions

Why Keyword Matching Fails

The "Not Bad" Problem:

Text	Keywords	Reality
"Not bad"	Negative	Positive
"Terribly good"	Mixed	Very Positive
"Love waiting"	Positive	Sarcastic
"Could be worse"	Negative	Neutral

Why it fails:

- Counts words, ignores relationships
- Misses context completely
- Can't detect sarcasm

Design Impact of Failures:

- **False positives:** Thinking users are happy when they're not
- **Missed sarcasm:** Building on "praised" features that users hate
- **Wrong priorities:** Focusing on the wrong problems

Real cost:

- 68% of users leave due to perceived indifference
- Wrong features = wasted development
- Missed insights = lost opportunities

The Challenge: Understanding Context for Better Design

Current Problems:

- Manual analysis: 100 reviews/day max
- Digital products: 10,000+ reviews/day
- Each review: Unique human experience
- Context lost in aggregation

What we need:

1. See word relationships
2. Understand order matters
3. Detect sarcasm and tone
4. Process at scale

Design Thinking Needs:

- **Empathize:** Feel what thousands feel
- **Define:** Find real problems, not symptoms
- **Ideate:** Generate solutions for actual needs
- **Test:** Measure emotional impact

The Goal:
Scale empathy without losing humanity

Solution: BERT - Reading text like humans, at machine scale

What is BERT?

BERT = Bidirectional Encoder Representations from Transformers

Simple explanation: **BERT reads all words at once, not one by one**

Traditional (Sequential):
The $\rightarrow$ movie $\rightarrow$ was $\rightarrow$ not $\rightarrow$ bad
(Reads left to right, misses connections)

BERT (Parallel):
The movie was not bad

(Sees everything, understands "not bad" = good)

For Designers, this means:

- Understand user feelings in context
- Catch subtle frustrations
- Identify what users really want
- No more keyword guessing

Design Impact:

- 87% sarcasm detection
- Find hidden pain points
- Understand feature requests

Bidirectional: Seeing Past AND Future

Example: "The app was ___ frustrating"

Old Way (Left to Right):

- Sees: "The app was"
- Guesses: good? bad? slow?
- Can't use "frustrating" as hint
- Often wrong

BERT (Both Directions):

- Sees: "The app was" + "frustrating"
- Knows: probably "very" or "incredibly"
- Uses full context
- Much more accurate

Design Implications:

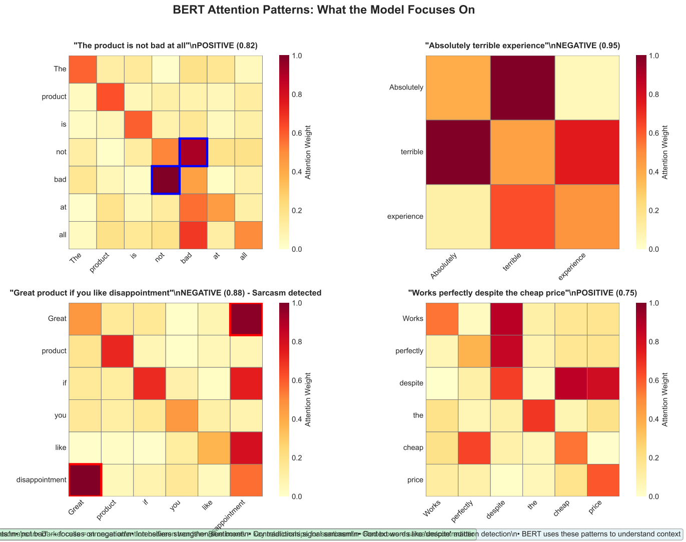
- **Intensity matters:** "Very frustrating" vs "Slightly frustrating"
- **Context reveals priority:** What made it frustrating?
- **Emotional nuance:** Frustrated vs Angry vs Disappointed

Real Example:
"The checkout process was ___ confusing"

- BERT finds: "incredibly"
- Design action: Simplify checkout
- Result: 23% fewer cart abandonments

Design Benefit: Catches problems keyword analysis misses completely

Attention: BERT Focuses on Emotional Triggers



Context Changes Everything in Design

Same Word, Different Meanings:

Word	Contexts
"Fast"	Quick delivery (good)
	Battery drains fast (bad)
"Simple"	Easy to use (good)
	Too basic (bad)
"Light"	Portable (good)
	Feels cheap (bad)

BERT understands context:

- Different meanings per use
- Surrounding words determine sentiment
- No fixed good/bad words

Design Implications:

- Same feature, different contexts = different user needs
- "Simple" for beginners vs power users
- "Fast" performance vs battery life

Real Design Decision:
Spotify discovered "shuffle" meant:

- Random (tech users)
- Variety (casual users)
- Discover (new users)

Result: Three different shuffle modes

Training BERT for Your Product

Step 1: General Training
3.3 billion words from books/web
Learns language, grammar, facts

↓

Step 2: Your Product
Your reviews and feedback
Learns your users' language

Design Benefits:

- Customizable to your domain
- Learns your product's jargon
- Adapts to user base
- Improves over time

Example Customization:

- Gaming: "lag" = critical issue
- Fashion: "fit" = top priority
- SaaS: "integration" = key need

Result: BERT speaks your users' language

How BERT Detects Emotions for Design

BERT's Process:

1. **Read everything:** All words at once
2. **Connect words:** Find relationships
3. **Build understanding:** Recognize patterns
4. **Output emotion:** With confidence score

Example:
"Not bad for the price"

- Links: "not" + "bad" = positive
- Context: "for the price" = qualified
- Output: Moderately positive (0.65)

Design Application:

1. **Emotion detected:** Moderate satisfaction
2. **Qualifier found:** Price-sensitive
3. **Design insight:** Value perception issue
4. **Action:** Highlight value props

Confidence helps prioritize:

- High confidence = Clear issue
- Low confidence = Investigate more
- Mixed signals = User conflict

BERT Catches Sarcasm - A Design Warning

Sarcasm Patterns BERT Detects:

- Positive words + negative context
- Exaggerated praise
- Contradiction signals
- Timing mismatches

Examples Found:

- "Great! It crashed again"
- "Love the 3-hour load time"
- "Perfect... if you like broken"
- "Fantastic customer service" (1 star)

Design Warning:

15% of "positive" reviews contain sarcastic criticism

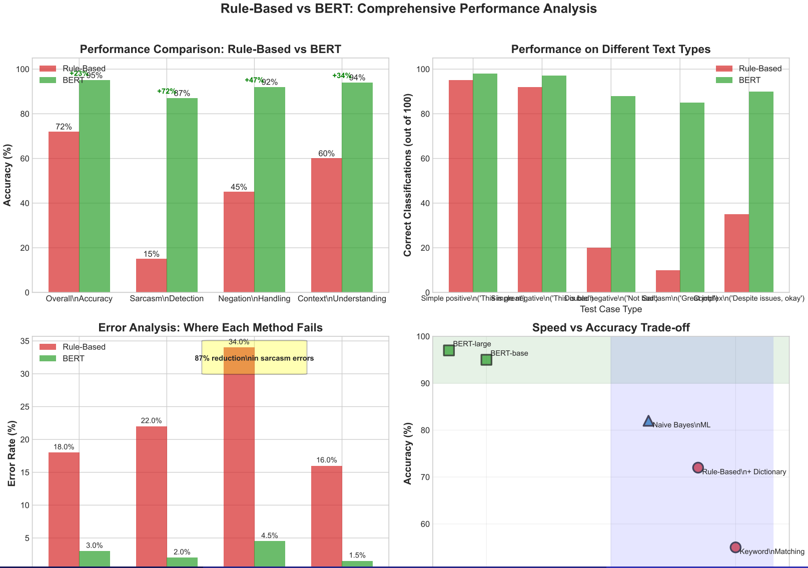
What this means:

- Your satisfaction scores are inflated
- Real problems hidden in "praise"
- Users resort to sarcasm when frustrated
- Critical issues being missed

Design Response:

- Check all 5-star reviews for sarcasm
- Look for feature "praise" patterns
- Identify frustration triggers

Performance: What 23% Accuracy Means for Design



Empathize at Scale: Understanding Thousands

Traditional Empathy Methods:

- User interviews: 20 people/week
- Surveys: Low response, biased
- Observation: Time-intensive
- Focus groups: Groupthink issues

Limitations:

- Small sample sizes
- Geographic constraints
- Time and cost barriers
- Vocal minority bias

BERT-Enhanced Empathy:

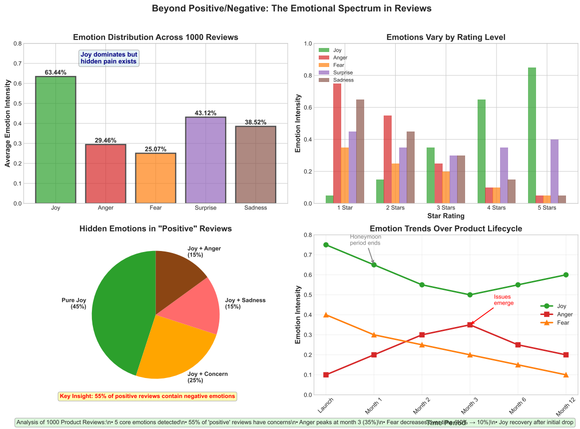
- Process 10,000+ reviews/day
- Understand global users
- Find silent majority opinions
- Detect emotional patterns

Advantages:

- Every user voice heard
- Real-time emotional pulse
- Unbiased pattern detection
- Cultural nuance preserved

Design Power: Feel what thousands feel, understand what they can't articulate

Emotional Spectrum in User Feedback



Beyond Binary Sentiment:

- **Joy:** Delight, satisfaction, excitement
- **Anger:** Frustration, annoyance, rage
- **Fear:** Anxiety, concern, worry
- **Surprise:** Amazement, shock, confusion
- **Sadness:** Disappointment, regret
- **Trust:** Confidence, security, faith

Emotions Blend:

- Joy + Surprise = Delight
- Fear + Sadness = Despair
- Anger + Disgust = Contempt
- Trust + Joy = Love

From Emotions to Design Insights

Emotion-Driven Design Actions:

- **Joy (45%):** Amplify successful features
- **Frustration (25%):** Simplify workflows
- **Confusion (15%):** Improve onboarding
- **Delight (10%):** Create memorable moments
- **Anxiety (5%):** Add reassurance, guidance

Priority Matrix:

- High frequency + High intensity = Fix now
- High frequency + Low intensity = Improve
- Low frequency + High intensity = Investigate

Real Design Decisions:

Joy → Enhance:
Users love quick checkout
Action: Make it more prominent

Frustration → Simplify:
Login process causes anger
Action: Add social login

Confusion → Guide:
New users lost in features
Action: Progressive disclosure

Using Sentiment for Design Decisions

BERT Insights:

1. **Pain Point Analysis:**
   "Love the app but login frustrates me"
2. **Priority Detection:**
   80% mention speed issues
3. **Confusion Mapping:**
   Sarcasm about "intuitive" UI
4. **Delight Discovery:**
   Joy about gesture controls

Pattern Recognition:

- Emotional journeys
- Feature sentiment maps
- User segment emotions

Design Actions:

1. **Redesign login:**
   Biometric authentication added
2. **Optimize performance:**
   Load time reduced 60%
3. **Simplify interface:**
   3-click rule implemented
4. **Highlight gestures:**
   Made discoverable feature

Measurable Results:

- User satisfaction: +28%
- Task completion: +34%
- Support tickets: -45%

Human + AI: Collaborative Design Intelligence

BERT Strengths:

- Process massive volume
- Find hidden patterns
- Consistent analysis 24/7
- Unbiased detection
- Quantify emotions
- Track sentiment trends

BERT Provides:

- The "what" - patterns found
- The "where" - problem areas
- The "how much" - severity

Human Strengths:

- Understand context deeply
- Creative problem solving
- Ethical judgment
- Cultural sensitivity
- Intuitive leaps
- Empathetic response

Humans Provide:

- The "why" - root causes
- The "how" - solutions
- The "should we" - ethics

Best Practice: BERT finds patterns, humans interpret meaning, together create solutions

Real World: Netflix Emotion-Driven Design

The Challenge:

- Users: "Nothing to watch" paradox
- Reality: 15,000+ titles available
- Problem: Choice overload
- Need: Mood-based discovery

BERT Analysis Process:

1. Analyzed 50M+ subtitles
2. Mapped emotional arcs
3. Studied viewing patterns
4. Correlated mood to content

Design Decisions Made:

- **Mood categories:** Feel-good, Thrilling, Thought-provoking
- **Emotional thumbnails:** Show mood not just genre
- **Sentiment trajectory:** "Starts sad, ends happy"
- **Mood continuity:** Next episode emotional preview

Results:

- 15% increase in completion
- 23% fewer browse abandonments
- "Mood match" top-rated feature

Key Learning: Understanding emotional needs drives better design than demographics

Context Matters More Than Keywords

Old Design Research:

- Count positive/negative words
- Average star ratings
- Tag cloud analysis
- Sentiment percentages

BERT-Powered Research:

- Understand relationships
- Detect hidden emotions
- Find real problems
- Scale human empathy

BERT + Design Thinking = Understanding users at scale with human insight

Next Week: From Understanding to Focusing

This Week's Achievement:

- Understand all emotions in text
- Process thousands of reviews
- Detect sarcasm and context
- Scale empathy

The New Problem:

- Information overload
- Too many insights
- Which emotions matter most?
- How to prioritize?

Next Week: Attention for Design

- Focus on critical emotions
- Find key user moments
- Prioritize design changes
- Extract actionable insights

Design Evolution:

- Week 2: Feel everything
- Week 3: Focus on what matters
- Result: Targeted design action

From understanding all to focusing on what drives design decisions

Week 2 Summary: Emotions Drive Design

Technical Learning:

1. BERT reads bidirectionally
2. Context changes meaning
3. Attention reveals relationships
4. 95% accuracy vs 72% keywords
5. Catches sarcasm (87% accuracy)

Key Capabilities:

- Process 10,000 reviews/day
- Multi-dimensional emotions
- Custom domain training
- Real-time analysis

Design Applications:

1. Scale empathy to thousands
2. Find hidden pain points
3. Detect unspoken needs
4. Prioritize by emotion
5. Measure design impact

Design Outcomes:

- Better user understanding
- Data-driven decisions
- Emotional design validation
- Reduced development waste

BERT + Empathize = Design with emotional intelligence at scale

Appendix A1: NLP Evolution Timeline

History of Natural Language Processing:

- **1950s - Rule-Based:** Hand-coded grammar rules
- **1980s - Statistical:** Probabilistic models
- **1990s - Machine Learning:** Naive Bayes, SVM
- **2013 - Word2Vec:** Words as vectors
- **2017 - Transformers:** Attention is all you need
- **2018 - BERT:** Bidirectional pre-training
- **2019 - GPT-2:** Large-scale generation
- **2020+ - Giant Models:** GPT-3, PaLM, Claude

Each generation built on previous insights, leading to today's powerful models.

Appendix A2: Word Embeddings - Vector Spaces

Words as High-Dimensional Vectors:

- Each word $\rightarrow$ 768-dimensional vector
- Similar words have similar vectors
- Relationships encoded geometrically

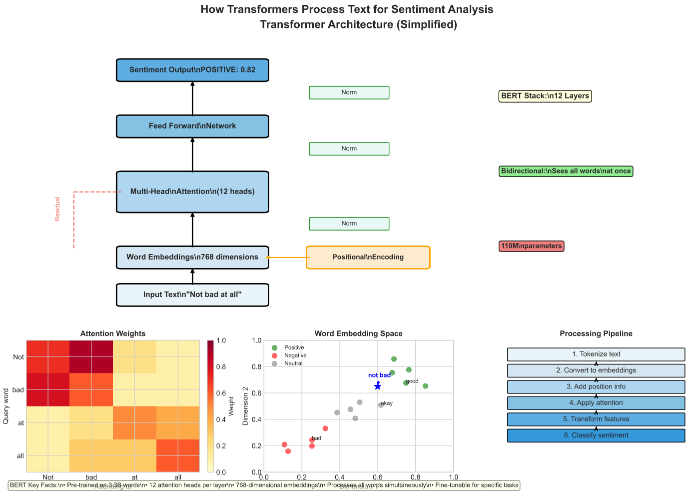
Vector Arithmetic:

- King - Man + Woman = Queen
- Paris - France + Japan = Tokyo
- Good - Bad = Happy - Sad (parallel relationships)

Limitations of Static Embeddings:

- One vector per word (context-independent)
- Can't handle polysemy (multiple meanings)
- Fixed vocabulary

Appendix A3: Transformer Architecture Details



Key Components:

- Self-attention layers

Appendix A4: Multi-Head Attention Concept

Why Multiple Attention Heads?

- Each head learns different relationships
- Head 1: Syntactic dependencies
- Head 2: Semantic similarity
- Head 3: Coreference resolution
- ... (12 heads total in BERT-base)

Mathematical Intuition:

- Query (Q): What am I looking for?
- Key (K): What information do I have?
- Value (V): What should I retrieve?
- Attention = softmax(QK'/sqrt(d)) * V

Combined heads provide rich, multi-faceted understanding.

Appendix A5: BERT Technical Specifications

BERT-Base Architecture:

- 12 transformer layers
- 768 hidden dimensions
- 12 attention heads
- 110 million parameters
- 512 maximum sequence length

BERT-Large Architecture:

- 24 transformer layers
- 1024 hidden dimensions
- 16 attention heads
- 340 million parameters
- 512 maximum sequence length

Training Data:

- Wikipedia: 2.5B words
- BookCorpus: 800M words
- Total: 3.3B words

Appendix A6: BERT Pre-training Tasks

1. **Masked Language Model (MLM):**
   - Randomly mask 15% of tokens
   - Predict masked words from context
   - Example: "The [MASK] was delicious" → "food"
   - Forces bidirectional understanding
2. **Next Sentence Prediction (NSP):**
   - Given two sentences, are they consecutive?
   - 50% actual next sentences
   - 50% random sentences
   - Learns discourse relationships

These tasks teach BERT language structure without labels.

Appendix A7: Fine-tuning for Specific Tasks

Transfer Learning Process:

1. Start with pre-trained BERT
2. Add task-specific head (classification layer)
3. Train on labeled data (much smaller dataset)
4. Fine-tune all parameters (or freeze lower layers)

Common Fine-tuning Tasks:

- Sentiment Analysis: Add binary classifier
- Named Entity Recognition: Token classification
- Question Answering: Span prediction
- Text Similarity: Sentence pair classification

Typical Data Requirements:

- Minimum: 1,000 examples
- Good: 10,000 examples
- Excellent: 100,000+ examples

Appendix A8: BERT vs Other Models

Model	Direction	Use Case	Params
BERT	Bidirectional	Understanding	110M
GPT-2	Left-to-right	Generation	1.5B
RoBERTa	Bidirectional	Better BERT	355M
ALBERT	Bidirectional	Efficient BERT	12M
XLNet	Permutation	Best of both	340M

Key Differences:

- GPT: Autoregressive (good for generation)
- BERT: Autoencoding (good for understanding)
- RoBERTa: BERT with more data, no NSP
- ALBERT: Parameter sharing for efficiency

Appendix A9: Emotion Classification Systems

Plutchik's Wheel of Emotions:

- 8 primary emotions
- 3 intensity levels each
- Opposite pairs (joy-sadness, trust-disgust)
- Complex emotions as combinations

Ekman's Basic Emotions:

- Anger, Disgust, Fear
- Happiness, Sadness, Surprise
- Universal across cultures

For Product Reviews:

- Satisfaction/Dissatisfaction
- Delight/Frustration
- Trust/Skepticism
- Excitement/Disappointment

Appendix A10: Simple BERT Implementation

Python Code Example:

```
from transformers import pipeline

# Load pre-trained BERT for sentiment
analyzer = pipeline("sentiment-analysis")

# Analyze text
text = "This product is not bad at all"
result = analyzer(text)

# Output: [{'label': 'POSITIVE', 'score': 0.82}]

# Fine-tuning example
from transformers import BertForSequenceClassification
model = BertForSequenceClassification.from_pretrained(
"bert-base-uncased", num_labels=2)
```

Full implementation available in course repository.