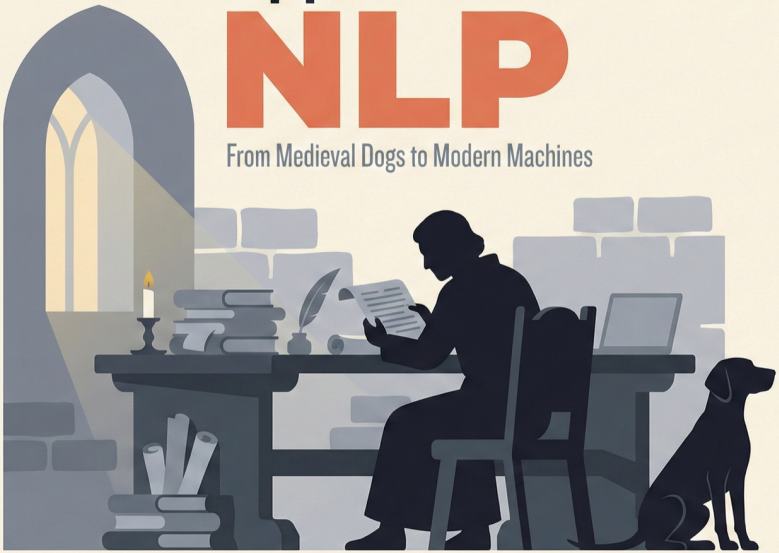
Applied NLP

From Medieval Dogs to Modern Machines



Two Tracks

Concepts first, systems second

Concepts & Intuition

We build mental models before code:

- representation (counts → vectors → context)
- matching and retrieval (what is relevant?)
- structure (how we turn text into analyzable data)

Goal: understand why each method works and fails.

Operations on Text

Treat text as a universal interface to documents, code, logs, and speech transcripts.

Classify → assign labels
Extract → schema/JSON fields
Retrieve → evidence at scale
Reason → synthesize + decide

We move from simple pipelines to advanced systems.

Roadmap

Methods evolve, and so do capabilities

Capability unlocks

- Better representation of meaning
- Better handling of context and ambiguity

What scales now

- extraction + labeling + retrieval at corpus scale
- hybrid workflows (classical + neural + LLM)

Each era adds tools; good systems combine them rather than replacing everything.

1

TF-IDF & Text Features

Word Counts & Information Theory

The foundation of text retrieval

- Text is unstructured — the hardest data type for machines
- First idea: just **count words**
- Problem: common words (“the”, “is”, “and”) dominate
- Solution: weight words by how informative they are

Information-Theory Lens

Self-information is $I(x) = -\log p(x)$: rare events carry more bits.
IDF is mathematically equivalent to self-information (surprisal).
In text: rarer terms are often more discriminative.

Shannon, 1948; Sparck Jones, 1972; Aizawa, 2003

Bag of Words

The simplest text representation

	climate	tax	merger	trial	chatbot	patent
“Climate patent trial update”	1	0	0	1	0	1
“Tax merger debate”	0	1	1	0	0	0
“Chatbot climate memo”	1	0	0	0	1	0

- Each document = a vector of word frequencies
- Ignores word order (“dog bites man” = “man bites dog”)
- But surprisingly effective for classification and retrieval

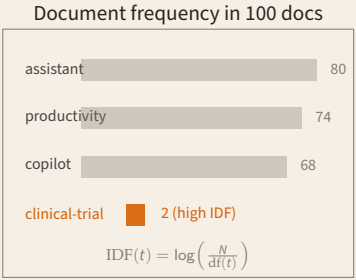
TF-IDF Intuition: Signal vs. Noise

What is distinctive in a noisy stream?

Imagine 100 AI company announcements this month.

- Most announcements repeat generic terms: **assistant**, **productivity**
- Those words are everywhere, so they barely distinguish documents
- One announcement includes clinical-trial evidence
- That rare term is a strong pointer to a specific sub-topic (health/biotech)

TF-IDF boosts words that are frequent *in this document* but rare *in the corpus*.



TF-IDF: The Math

$$w(t,d) = \underbrace{\mathrm{tf}(t,d)}_{\text{term frequency}} \times \underbrace{\log\left(\frac{N}{\mathrm{df}(t)}\right)}_{\text{inverse document frequency}}$$

Term	TF in doc	DF (of 1000)	IDF	TF-IDF
“assistant”	10/100	980	$\log(1.02) \approx 0.02$	0.002
“productivity”	7/100	720	$\log(1.39) \approx 0.33$	0.023
“clinical”	3/100	35	$\log(28.6) \approx 3.35$	0.101
“oncology”	2/100	8	$\log(125) \approx 4.83$	0.097

Common terms get low weight; domain-specific rare terms dominate TF-IDF signal.

TF-IDF: A Worked Example

Numerical intuition with one announcement

Suppose one document has 80 tokens and discusses a clinical AI launch.

Term	TF	DF/1000	IDF	TF-IDF	Interpretation
assistant	8/80	950	0.05	0.005	very common term, weak signal
productivity	5/80	700	0.36	0.023	moderately informative
clinical	3/80	35	3.35	0.126	rare and highly distinctive
oncology	2/80	8	4.83	0.121	very rare, high signal

Key idea: a term can appear fewer times but still dominate if it is globally rare.

BM25: TF-IDF's Descendant (Still Alive in 2026)

The algorithm that powers search engines

- BM25 adds **term frequency saturation**: $\frac{\text{tf}}{\text{tf}+k_1}$
- Prevents long documents from dominating
- Default in **Elasticsearch**, Apache Solr, Apache Lucene

2024: BMX — The Next Step

BMX combines entropy-weighted similarity with TF-IDF.
Outperforms BM25 on the BEIR benchmark.
See Li et al., 2024 (arXiv:2408.06643).

Lesson: foundational methods don't die — they evolve.
Every modern search engine still uses TF-IDF descendants.

Robertson et al., 1994; Robertson & Zaragoza, 2009; Li et al., 2024

2

Topic Modeling

Uncovering Hidden Relationships

From words to latent structure

LSA / LSI

SVD on term-document matrix.
Captures global co-occurrence.
Deerwester et al., 1990

LDA

Probabilistic generative model.
Documents as topic mixtures.
Blei et al., 2003

NMF

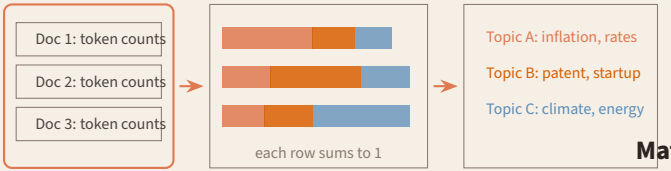
Non-negative factorization.
Usually easier to interpret.
Lee & Seung, 1999

- Method evolution: algebraic compression $\rightarrow$ probabilistic semantics $\rightarrow$ interpretable factorization.
- In social science: LDA became a workhorse, but evaluation remains partly subjective.
- Practical rule: judge quality by coherence, usefulness for the question, and human interpretability.

Deerwester et al., 1990; Blei et al., 2003; Lee & Seung, 1999

Matrix Factorization

An intuitive map: documents → topics → words



Equivalent views:

- documents become weighted topic profiles
- each topic is a weighted word profile

Matrix view:

$$A_{\text{docs} \times \text{words}} \approx W_{\text{docs} \times \text{topics}} \cdot H_{\text{topics} \times \text{words}}$$

- **W**: “how much of each topic in each document”
- **H**: “which words define each topic”

Deerwester et al., 1990; Lee & Seung, 1999

Topic Modeling: Policy Text to Topic Proportions

Topics

Macroeconomy

`inflation 0.09, interest 0.07, growth 0.05`

Innovation and AI

`productivity 0.06, automation 0.05, patent 0.04`

Climate Policy

`emissions 0.05, carbon 0.04, transition 0.03`

Health and Biotech

`trial 0.04, hospital 0.03, vaccine 0.02`

Documents

ECB Brief: Inflation, AI Productivity, and Green Transition

inflation is an dolor sit amet, consectetur insurtinn economier education value of roes and interest rates market economic, characteristric. Contact whole efficient notemat important opensration narrals for productivity gains, anown deirity and automation major swnis ned firea. Consimulation and potentiais oc sninon monam projecs to lovenise loial health growth, ea commodo consequat.

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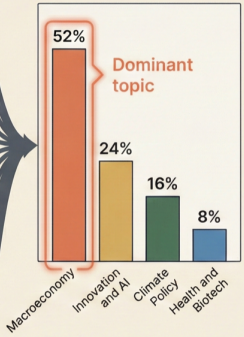
Topic proportions and assignments



Macroeconomy dominates this document (52%). Remaining topics still contribute meaningful context.

Discovering Topics in Text

Automatic theme extraction from a large corpus

Feed 10,000 documents into a topic model → four coherent themes:

Technology

AI, startup, funding, platform, compute, deploy

Climate

emissions, carbon, renewable, ESG, transition, green

Economics

inflation, GDP, labor, trade, policy, fiscal

Health

vaccine, trial, patients, drug, biotech, FDA

An article on “AI for drug discovery”: 50% Technology, 30% Health, 20% other

Documents are mixtures, not single labels.

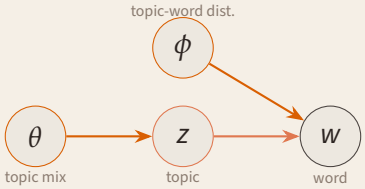
LDA: The Generative Model

Formal process + plain-language intuition

Generative story

1. Draw document topic mix: $\theta_d \sim \text{Dir}(\alpha)$
2. For each token position n, sample a topic: $z_{d,n} \sim \text{Mult}(\theta_d)$
3. Sample a word from that topic: $w_{d,n} \sim \text{Mult}(\phi_{z_{d,n}})$

Intuition: pick a theme, then pick a word typical for that theme.

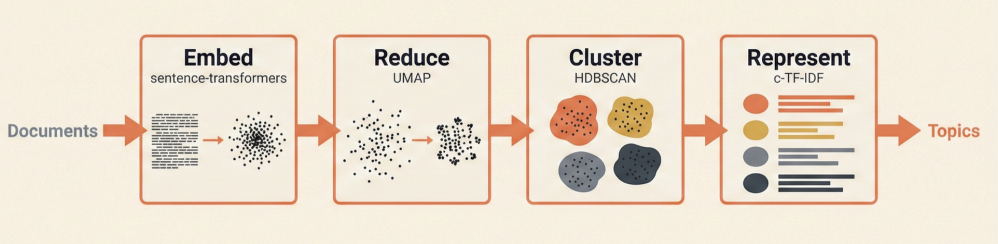


Example token flow:
`[Topic=Health]` → `vaccine`
`[Topic=Economics]` → `inflation`

Blei, Ng & Jordan, 2003

BERTopic: Topic Modeling for 2026

Embeddings + clustering + interpretability



Advantages over LDA:

- Auto-selects topic count
- 50+ languages
- LLM-assisted topic labels
- Local models run on laptops (privacy + cost)

Benchmark:

- Coherence (Cv): 0.76 vs LDA 0.38 ($\sim 2\times$)
- Strong open-source ecosystem + notebook tooling
- New releases: multi-GPU and Model2Vec support

Grootendorst, 2022; arXiv:2203.05794

BERTopic in Practice

Why social scientists love it

- Interpretable: c-TF-IDF gives real words per topic (not just topic IDs)
- Scalable: handles 100K+ documents on a laptop
- LLM integration: feed topic words to GPT/Claude for human-readable names
- Visualization: built-in topic maps, hierarchies, temporal trends
- Local-first option: strong small/local models can label topics offline

Bridge to Social Science

BERTopic is the most adopted topic model in social science since LDA.
Used in: innovation studies, policy analysis, media research, scientometrics.

We'll build a full BERTopic pipeline in NB04, including a topic map and LLM topic naming.

3

Word Embeddings & Vector Space

Words as GPS Coordinates

From sparse counts to dense meaning

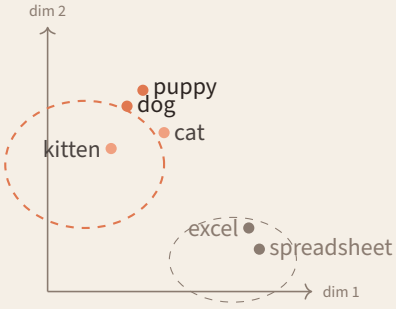
TF-IDF: each word = a dimension (10,000+ dims)

Word2Vec: each word = a **dense vector** (100–300 dims)

Think of it as GPS coordinates in meaning-space:

- "dog" and "puppy" are nearby
- "dog" and "spreadsheet" are far apart
- Similar meanings → similar coordinates

Distributional idea: "you know a word by the company it keeps." Meaning emerges from context at scale.

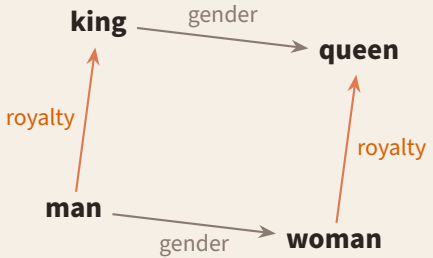


Mikolov et al., 2013

Vector Arithmetic

The most famous equation in NLP

$$\vec{\text{king}} - \vec{\text{man}} + \vec{\text{woman}} \approx \vec{\text{queen}}$$



Works for: Paris − France + Germany ≈ Berlin

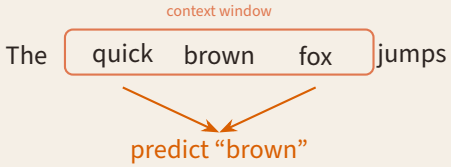
Captures relational structure, not just similarity.

How Word2Vec Learns

Predicting context from massive text corpora

The model reads thousands of books, predicting words from context:

"The dog fetched the [_____] from the garden."



- **Skip-gram**: predict context from center word
- **CBOW**: predict center word from context
- Words that appear in similar contexts get similar vectors

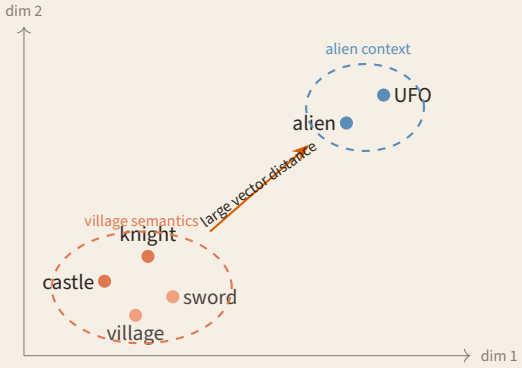
Mikolov et al., 2013; Pennington et al. (GloVe), 2014

The UFO in the Village

Distance = dissimilarity in vector space

- Frequent co-occurrence pulls vectors together.
- Rare concepts with different context drift far away.
- Distance in embedding space approximates semantic distance.

Distributional hypothesis: “You shall know a word by the company it keeps.” If “UFO” rarely appears with village-life terms, it lands in a different region.



Visualizing Embedding Space

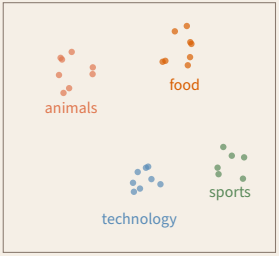
From 300 dimensions down to 2

Dimensionality reduction:

- **t-SNE**: preserves local structure
- **UMAP**: preserves global + local
- Both: 300D $\rightarrow$ 2D for visualization

What you see:

- Semantic clusters (animals, food, tech)
- Analogies as parallel lines
- Outliers = unusual words



t-SNE / UMAP projection

Bias in Embeddings

A warning for social scientists

- Word2Vec trained on Google News:
  - "man" $\rightarrow$ "computer programmer"
  - "woman" $\rightarrow$ "homemaker"
- Embeddings absorb and amplify societal biases from training data
- WEAT test: measures stereotypes in embedding space

For Social Scientists

This is both a **bug** and a **feature**:
— Bug: biased models produce biased outputs
— Feature: embeddings measure cultural associations at scale

Bolukbasi et al., 2016; Caliskan et al., 2017; Kozlowski et al., 2019

From Words to Sentences

Sentence-BERT and the MTEB era

- Word2Vec: one vector per *word*
- Sentence-BERT: one vector per sentence/paragraph
- **MTEB** = Massive Text Embedding Benchmark
- Multilingual embeddings map similar meaning across languages into nearby regions

Practical speedup: pairwise semantic search drops from hours to seconds with bi-encoder embeddings.

Provider landscape:

- API: OpenAI, Gemini, xAI/Grok (where available)
- Local/open: SBERT, BGE, E5, LLM-derived embeddings
- Ollama + HF pipelines for local-first workflows

Ops tips:

- Batch embedding APIs for cost/performance
- Cache vectors and version your embedding model

Reimers & Gurevych, 2019

4

Transformers

Attention Is All You Need

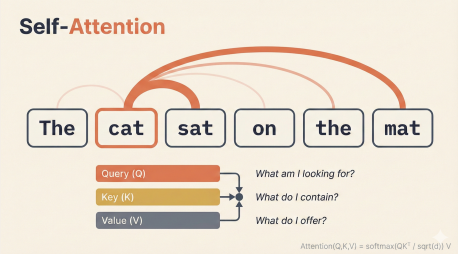
The paper that changed everything

Why attention was needed:

- RNN-style models are sequential and brittle on long-range dependencies
- Attention lets each token directly weigh other tokens
- Computation becomes parallel and more context-rich

Self-attention: each token scores all others through Q/K/V.

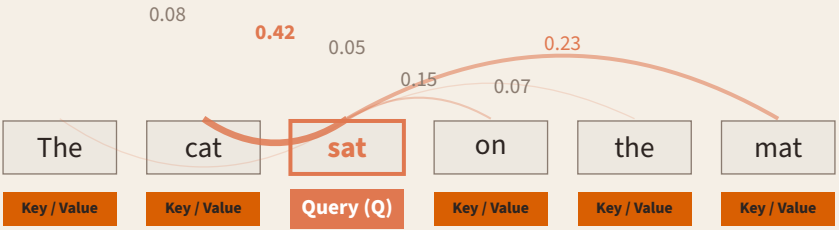
Query: what to look for; **Key**: what each token contains; **Value**: what it contributes.



Vaswani et al., 2017

Self-Attention: How Tokens Attend to Each Other

“The cat sat on the mat” — which words matter for “sat”?

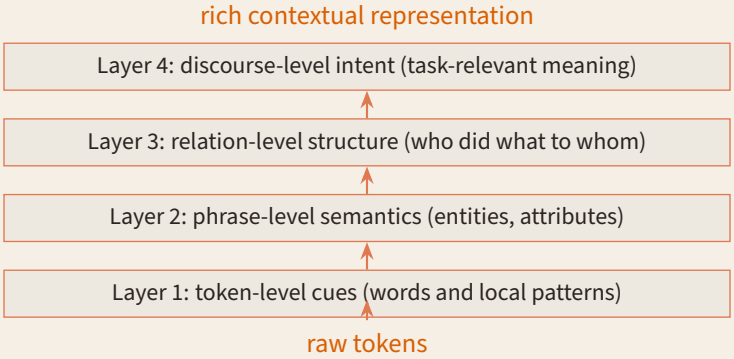


Reading the diagram:
Line thickness = attention weight.
“sat” attends most to **“cat”** (the subject) and **“mat”** (the location).

Key insight:
Every token can attend to every other token — no sequential bottleneck.
Context is captured *in parallel*.

The Playlist Curation Analogy

Each transformer layer adds context



Like curating a playlist: each pass adds signal until the final ranking reflects deeper context.

Three Transformer Architectures

Architecture	Direction	Models	Tasks
Encoder-only	$\leftrightarrow$ bidirectional	BERT, RoBERTa	Classification, NER, similarity
Decoder-only	$\rightarrow$ left-to-right	GPT, Claude, Llama	Generation, chat, reasoning
Enc-Decoder	$\leftrightarrow + \rightarrow$	T5, BART	Translation, summarization

BERT: Understanding

Uses bidirectional context via masked-token training.
"I went to the **bank**"
$\rightarrow$ river bank? financial bank?
BERT uses *full context* to decide.

GPT: Generation

Predicts the *next word*.
"Smartphone autocomplete on steroids."

Counter: "Saying LLMs just predict the next word is like saying a cathedral is just a pile of stones."

Devlin et al., 2019; Radford et al., 2019; Raffel et al., 2020

The Evolution of Text Similarity

Same sentences, different representations

	TF-IDF	Word2Vec	SBERT
“Startup raises funding” vs “Company secures capital”	0.12	0.71	0.88
“AI lab cuts costs” vs “Model training becomes cheaper”	0.08	0.66	0.84
“python script failed” vs “python snake escaped”	0.21	0.49	0.09

TF-IDF

Word overlap only.
“puppy” $\neq$ “dog”

Word2Vec

Semantic similarity.
“puppy” $\approx$ “dog”

SBERT

Contextual meaning.
Disambiguates “bank”

5

2025/2026 State of the Art

The LLM Landscape

February 2026

OpenAI	Anthropic	Google	Mistral
GPT-5.2, o3 Codex 5.3	Claude Opus 4.6	Gemini 3	Large 3
Meta	**DeepSeek**	**Qwen**	**xAI**
Llama 4	V3.2, R1	Qwen 3	Grok

Key shift: DeepSeek/Qwen accelerated Chinese AI adoption from 1.2% → 30% global usage share in one year.

Stanford HAI 2025: Chinese developers 17.1% of HuggingFace (vs US 15.8%). 63% of fine-tuned models use Chinese bases.

The Model Zoo

Key specifications, early 2026

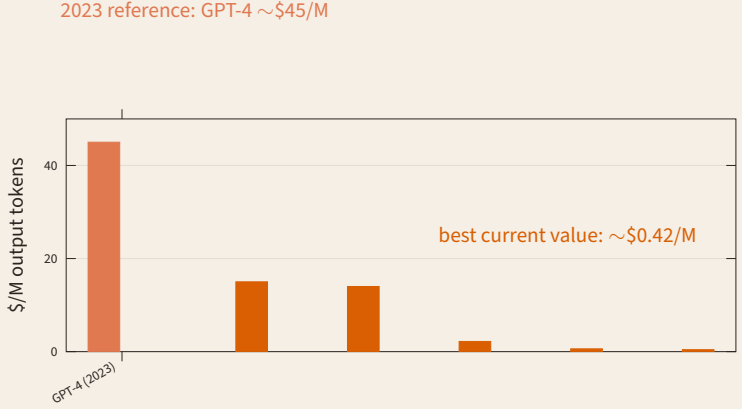
Model	Context	Strength	Input $/M	Note
GPT-5.2	400K	Reasoning	$1.75	100% AIME
Claude Opus 4.6	200K	Coding	$3.00	77% SWE-bench
Gemini 3 Pro	2M	Multimodal	varies	1501 LMArena Elo
Llama 4 Scout	10M	Open-source	free	17B active/109B
DeepSeek V3.2	128K	Cost	$0.27	37B active/671B
Qwen 3	128K	Multilingual	free	119 languages

Llama 4 Scout: 10M tokens ≈ **15,000 pages** in one prompt.

Google: near-perfect needle-in-a-haystack across text, 10.5h video, 107h audio.

The Cost of Intelligence is Collapsing

100× cheaper in 2 years



Approximate list-price comparison; representative provider list prices.

Reasoning Models: Think Longer, Not Bigger

The paradigm shift of 2024–2025

The idea: spend more compute at *inference time* instead of making models bigger.

- **o1** (Sep 2024): internal chain-of-thought
- **o3** (Apr 2025): 87.5% ARC-AGI
- **QwQ** (Nov 2024): early open reasoning release
- **DeepSeek-R1**: mainstream breakout (not first)

Key finding (Snell et al., 2024):

A smaller model with more inference compute outperforms a 14× larger model that answers instantly.

Visible reasoning:

- OpenAI: hidden CoT
- DeepSeek: `<think>...</think>`
- Transparent vs hidden

Wei et al., 2022; Snell et al., 2024

DeepSeek: The Earthquake

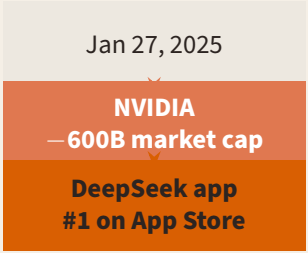
January 2025 — the day NVIDIA lost $600B

DeepSeek-V3 (Dec 2024):

- MoE: 671B total, 37B active (∼5.5%)
- Training cost: $5.6M on 2,048 H800 GPUs
- vs GPT-4 estimated $50–100M
- Engineers coded in **PTX** (GPU assembly)
- FP8 mixed-precision at extreme scale

DeepSeek-R1 (Jan 2025):

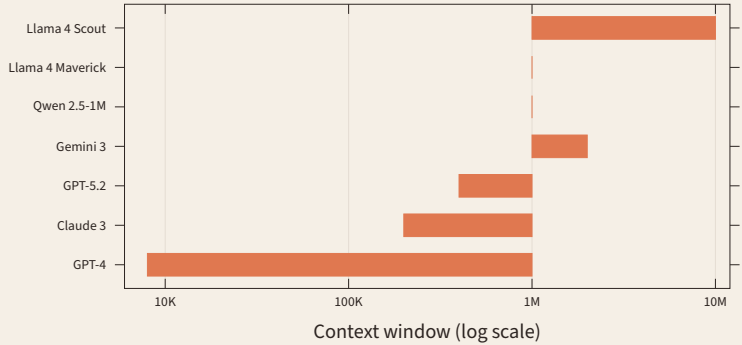
- **Pure RL** (no supervised fine-tuning)
- Matches o1 at 90–96% lower cost
- **MIT license** — fully open
- 32B distilled model beats o1-mini



"Scarcity fosters innovation"
— Brookings Institution

Context Windows in 2026

From 4K tokens to 10M tokens in 3 years



Log scale reveals both mainstream (100K–2M) and frontier (10M) ranges.

Structured Output: LLMs as Data Extraction Engines

Not just chat — structured data

LLMs can return guaranteed JSON:

- Constrained decoding
- Pydantic schema validation
- Retry on parse failure

Tools:

- OpenAI Structured Outputs
- `instructor` library (3M+/mo)
- `outlines` (token-level FSM)

```python
class ArticleInfo(BaseModel):
    title: str
    key_people: list[str]
    sentiment: Literal[
        "positive", "negative",
        "neutral"
    ]
    topics: list[str]
    confidence: float

# LLM returns valid JSON
# matching this schema
```

We'll build this in NB03 — extracting structured data from news articles.

The Benchmark Landscape

MMLU is saturated — what's next?

Saturated (90%+ for top models):

- MMLU
- HellaSwag
- ARC-Challenge

Still differentiating:

- **GPQA Diamond**: PhD-level science
  Gemini 3: 91.9%
- **AIME**: Math olympiad
  GPT-5.2: 100%
- **SWE-bench**: Real GitHub issues
  Claude Opus 4.6: 77.2%

The new frontier:

Humanity's Last Exam (HLE)
Published in *Nature*, 2025

- 1,000 experts, 500+ institutions
- 2,500 questions, 100+ subjects
- Jan 2025: top models $<10\%$
- Feb 2026: Gemini 3 Pro: 37.2%
- GPT-5.2: 35.4%
- Human experts: $\sim 90\%$

Hendrycks et al., 2025 (Nature); scale.com/leaderboard

Multimodal AI

Text, images, video, audio — in one model

Vision foundations:

- **CLIP** (2021): text + images in same vector space
- Vision-Language Models: GPT-4o, Gemini, Claude see images natively
- Open: Qwen2.5-VL, LLaMA 3.2 Vision

Image generation:

- FLUX, GPT Image 1.5, Midjourney V7
- Accurate text in images (Ideogram 3.0)

Video generation (2025–26):

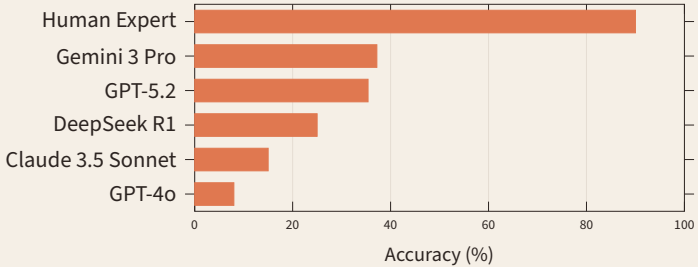
- Sora 2: longer clips + synchronized audio
- Kling 3.0: native 4K 60fps demos
- Veo 3.1 and WAN 2.6 (open)

Audio/Speech:

- Qwen3-TTS: strong open speech synthesis
- Kokoro: lightweight local TTS
- Whisper large-v3: robust ASR
- ElevenLabs v3: multilingual voice generation

Humanity's Last Exam

1,000 experts. 100+ subjects. Best AI still below 40%.



Coding frontier (2026)

Coding evals (SWE-bench style and GPT-Val variants) are now key differentiators; practical software engineering remains a live benchmark race.

Nature, 2025; arXiv:2501.14249

6

Applied Social Science

NLP for Economists & Social Scientists

Text as Data

- **Gentzkow, Kelly & Taddy** (2019): “Text as Data” — canonized the field
- **Ash & Hansen** (2023): first major econ survey on embeddings + transformers
- Social science is adopting NLP with a 4-year diffusion lag

What NLP enables for social science:

- Scale: analyze 100,000+ documents (policy, patents, speeches)
- Measurement: cultural dimensions from text (Kozlowski et al., 2019)
- Replication: LLMs outperform crowd-workers for annotation (Gilardi et al., 2023)
- Simulation: “Homo Silicus” — LLMs as simulated survey respondents (Horton, 2023)

Gentzkow et al., 2019 (JEL); Ash & Hansen, 2023 (Ann. Rev. Econ.)

Embeddings for Innovation Research

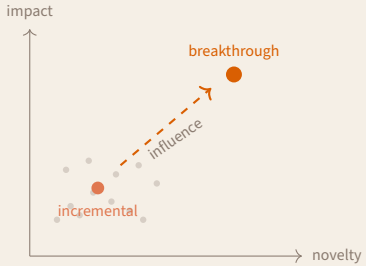
Measuring technological change with text

Patent similarity (Arts et al., 2018, 2021):
TF-IDF + cosine on patent text to measure technological relatedness

Breakthrough detection (Kelly et al., 2021):
A patent is "important" if *textually distant* from prior work but *similar to subsequent*. Covers 1840–present!

PatentSBERTa (Bekamiri, Hain & Jurowetzki, 2024):
Fine-tuned SBERT on patent pairs for semantic patent matching

NLP + economic geography: map knowledge spaces and identify smart-specialization opportunities.



AI & Productivity: The Evidence

Three landmark experiments

BCG + Harvard
Dell'Acqua et al., 2023

758 consultants

+25% faster
+40% quality
within AI's frontier

–19% quality
outside frontier

Lowest performers:
+43% improvement

MIT / Science
Noy & Zhang, 2023

453 professionals

–40% time
+18% quality

Greatest benefits for
lower-ability workers

Published in *Science*

Stanford / QJE
Brynjolfsson et al., 2023

5,172 CS agents

+14% overall
+34% for novices

AI disseminates
tacit knowledge
of top performers

Published in *QJE*

Pattern: AI is an *equalizer* — biggest gains for least experienced workers.

The Adoption Gap

Social science is catching up — fast

Why the lag?

- Interpretability requirements
- Causal identification culture
- Smaller datasets / qualitative traditions
- Institutional inertia

Why it's closing:

- BERTopic: interpretable by design
- Structured output: LLM $\rightarrow$ DataFrame
- Cost collapse: everyone can afford it
- Embedding-based measurement at scale

The Jagged Frontier (Dell'Acqua et al.)

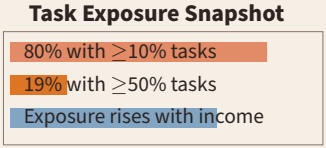
AI excels at some tasks, fails at others — and the boundary is jagged.
The professional skill is knowing *when* to use AI and when not to.

Who Is Affected?

AI task exposure across the economy

Eloundou et al. (2024, *Science*):

- ∼80% of US workforce: ≥10% of tasks affected
- ∼19%: ≥50% of tasks affected
- Higher-income jobs face greater exposure



Acemoglu (2024 Nobel laureate):
"The Simple Macroeconomics of AI"
Estimate: ≤0.66% TFP increase over 10 years

Modest macro effect, but large for specific tasks and workers.

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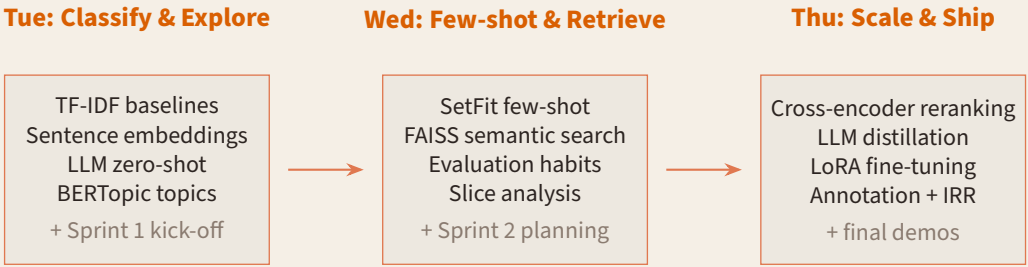
Workshop Preview & Closing

What We'll Build This Week

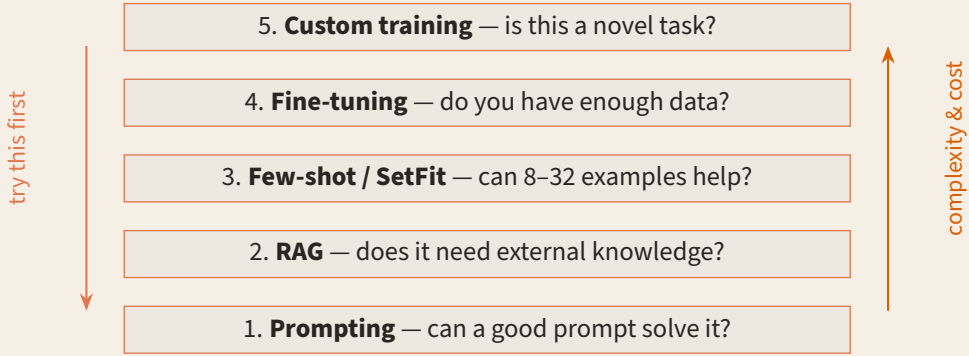
Tue–Wed–Thu: five blocks, eleven notebooks



Build, compare, and validate: each day adds complexity to your NLP toolkit.

The Professional's Playbook

Start simple, escalate only when needed



Most real-world NLP problems are solved at levels 1–2.

Five Themes to Remember

1. **Foundational methods haven't been replaced**
   TF-IDF lives in BM25. Embeddings are the backbone of search.
2. **The reasoning revolution**
   Inference-time compute and transparent reasoning changed model behavior.
3. **The cost of intelligence is collapsing**
   Frontier-level capability is becoming dramatically cheaper year by year.
4. **Local, privacy-first NLP is now practical**
   Strong laptop-grade models make private analysis feasible for many teams.
5. **The adoption gap is closing**
   Social science is still behind CS, but adoption is accelerating with usable tooling.

Resources & Further Reading

Textbooks:

- Grimmer, Roberts & Stewart (2022)
  Text as Data (Princeton UP)
- Jurafsky & Martin
  SLP 3rd ed. (free online)
- Raschka (2024)
  Build an LLM From Scratch

Visual guides:

- Jay Alammar's Illustrated Series
- 3Blue1Brown Transformer videos
- HuggingFace LLM Course

Key papers for social science:

- Gentzkow et al. (2019) — JEL
- Ash & Hansen (2023) —
  Ann. Rev. Econ.
- Kozlowski et al. (2019) — ASR
- Gilardi et al. (2023) — annotation
- Dell'Acqua et al. (2023) —
  productivity

This course:

`github.com/RJuro/unistra-nlp2026`
`rjuro.github.io/unistra-nlp2026`

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Attention is all you need.
In *Advances in Neural Information Processing Systems 30 (NeurIPS 2017)*, pages 5998–6008.

Let’s begin.

20 hours to build your NLP toolkit.

Roman Jurowetzki — roman@business.aau.dk