AI and Unstructured Data for Measurement and Estimation

Lecture 1: Large Language Models

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Background Reading

[Gentzkow et al., 2019a] (pre-LLM methods)

[Ash and Hansen, 2023] (transition period)

[Ash et al., 2025] (LLM methods)

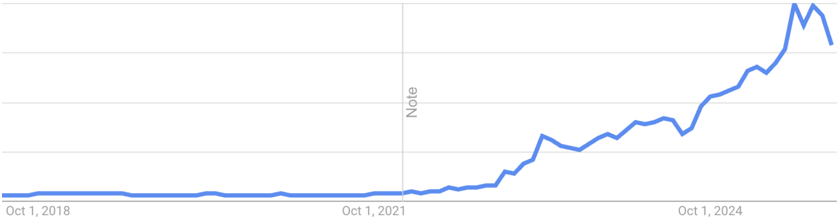
[Ludwig et al., 2025] (LLM methods)

[Jurafsky and Martin, 2025] textbook `https://stanford.io/4qkv65V`

1. Word embeddings, chapter 5
2. LLMs, chapter 7, 8, 10

Outline

Google Trends: "Artificial Intelligence"



Unstructured Data for Economic Measurement

Typical motivation for using unstructured data in economics is to measure some observation-specific latent variable θ_i.

Examples include:

1. [Baker et al., 2016]
   θ_i: economic policy uncertainty; data: newspaper text.
2. [Gentzkow et al., 2019b]
   θ_i: polarization; data: Congressional Records.
3. [Bandiera et al., 2020]
   θ_i: CEO behavior; data: time use surveys.
4. [Adukia et al., 2023]
   θ_i: cultural representation; data: children's book photos.
5. [Gorodnichenko et al., 2023]
   θ_i: Fed chairperson tone; data: FOMC press conference audio feed.

How Does AI Change the Landscape?

Potentially improves estimation of θ_i.

Reduces the time cost of extracting information from unstructured data.

Brings unstructured data analysis more into the mainstream.

Need to better understand statistical properties of empirical pipelines that incorporate AI.

Lecture Plan

Lecture I: Foundation LLM/AI models.

Lecture II: Adapting foundation models for economic measurement.

Lecture III: AI/ML-generated estimates $\widehat{\theta}_i$ in regression models.

All material on
`https://github.com/sekhansen/columbia_lectures_2025`.

Outline

Notation

The corpus is composed of D documents indexed by d.

After pre-processing, each document is a finite, length-N_d list of terms $\mathbf{w}_d = (w_{d,1}, \dots, w_{d,N_d})$ with generic element $w_{d,n}$.

Suppose there are V **unique** terms in the corpus, indexed by v.

We can then map each term in the corpus into this index, so that $w_{d,n} \in \{1, \dots, V\}$.

Example

Consider three documents:

1. ‘stephen is nice’
2. ‘john is also nice’
3. ‘george is mean’

We can consider the set of unique terms as $\{\text{stephen}, \text{is}, \text{nice}, \text{john}, \text{also}, \text{george}, \text{mean}\}$ so that $V = 7$.

Construct the following index:

stephen	is	nice	john	also	george	mean
1	2	3	4	5	6	7

We then have $\mathbf{w}_1 = (1, 2, 3)$; $\mathbf{w}_2 = (4, 2, 5, 3)$; $\mathbf{w}_3 = (6, 2, 7)$.

Document-Term Matrix

In the bag-of-words model, we summarize the information in a corpus via term counts.

Let $x_{d,v}$ be the count of term v in document d. The document-term matrix $\mathbf{X}$ collects the counts $x_{d,v}$ into a $D \times V$ matrix.

In the previous example, we have

$$\mathbf{X} = \begin{bmatrix} 1 & 1 & 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 1 & 1 & 1 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 1 & 1 \end{bmatrix}$$

Limitations of Bag-of-Words

Synonomy

economic growth is weak but long-term productivity trends are strong
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Sequence

economic growth is weak but long-term productivity trends are strong
economic growth is strong but long-term productivity trends are weak

Older is Sometimes Better! [Plaza-del-Arco et al., 2024]

Task/Language		best ZSL	supervised Standard ML	supervised Transformer
SA	EN	0.553	0.610	**0.680**
	DE	0.517	0.610	**0.677**
	FR	0.528	0.612	**0.706**
AC-Gender	EN	0.624	0.601	**0.638**
	DE	0.497	0.540	**0.629**
	FR	0.579	0.546	**0.650**
AC-Age	EN	0.572	0.620	**0.636**
	DE	0.503	0.602	**0.611**
	FR	0.550	0.540	**0.568**

Outline

Language as Vectors

At a very high level, an LLM takes an input text and coverts it into a (relatively) low dimensional vector.

This vector might be of interest in its own right, e.g. document similarity.

Or it might be an intermediate representation for a different language task, e.g. predicting an associated label or predicting new words.

LLMs allow the vector representation to change when the word sequence changes to capture meaning.

Word Embeddings

A word embedding is a low-dimensional vector representation of a word.

Ideally in this low-dimensional vector space words with similar meanings will lie close together.

The construction of word embeddings was an important precursor to the development of large language models.

Self-Supervised Learning

The ‘meaning’ of a word is an unobserved and subjective concept.

Difficult to directly formulate an objective function.

Important conceptual idea is to formulate word prediction tasks that are solved using word embeddings.[1]

The approach of using auxiliary word prediction tasks to build high-quality embeddings is called self-supervised learning.

[1]See also [Bengio et al., 2003].

Distributional Hypothesis

The distributional hypothesis states that words that share similar contexts share similar meanings.

Example from Jurafsky and Martin:

(6.1) Ongchoi is delicious sauteed with garlic.

(6.2) Ongchoi is superb over rice.

(6.3) ...ongchoi leaves with salty sauces...

And suppose that you had seen many of these context words in other contexts:

(6.4) ...spinach sauteed with garlic over rice...

(6.5) ...chard stems and leaves are delicious...

(6.6) ...collard greens and other salty leafy greens

Formalizing Local Context

The *context* of $w_{d,n}$ is a length-$2L$ window of words around $w_{d,n}$:

$$\mathsf{C}(w_{d,n}) = [w_{d,n-L}, w_{d,n-L+1}, \ldots, w_{d,n+L-1}, w_{d,n+L}]$$

In line with distributional hypothesis, word embedding models seek to generate similar embeddings for words that share similar contexts.

Word2Vec

Word2vec [Mikolov et al., 2013a, Mikolov et al., 2013b] is a particularly well-known algorithm for the construction of word embeddings.

Important example of a neural-network-based language model that was scalable and effective.

Skipgram Variant

1. Predict presence of each $w_{d,n-l} \in \mathrm{C}(w_{d,n})$ given $w_{d,n}$.
2. Predict absence of randomly sampled words from the corpus given $w_{d,n}$.

Words and Context in Skipgram Model

"economic growth is weak but long-term productivity trends are strong"

Suppose $L = 2$.

Positive Examples		**Negative Examples**	
Word	Context	Word	Context
economic	growth	economic	down
economic	is	economic	towards
growth	economic	growth	inflation
growth	is	growth	mild
growth	weak	growth	very
is	economic	is	not
is	growth	is	can
is	weak	is	rate
is	but	is	how
.	.	.	.
strong	are	strong	many

The number of negative examples to sample per positive example is a modeling choice.

Parametrization of the Prediction Problems

Endow each word v in the vocabulary with an embedding vector $\boldsymbol{\rho}_v \in \mathbb{R}^K$ and a context vector $\boldsymbol{\alpha}_v \in \mathbb{R}^K$ where $K \ll V$.

The positive examples are modeled as

$$\Pr\left[\, w_{d,n-l} \in \mathrm{C}(w_{d,n}) \mid w_{d,n} \,\right] = \frac{\exp\left(\boldsymbol{\rho}_{w_{d,n}}^T \boldsymbol{\alpha}_{w_{d,n-l}}\right)}{1 + \exp\left(\boldsymbol{\rho}_{w_{d,n}}^T \boldsymbol{\alpha}_{w_{d,n-l}}\right)}$$

and the negative examples are modeled as

$$\Pr\left[\, w_{d,n-l} \notin \mathrm{C}(w_{d,n}) \mid w_{d,n} \,\right] = 1 - \frac{\exp\left(\boldsymbol{\rho}_{w_{d,n}}^T \boldsymbol{\alpha}_{w_{d,n-l}}\right)}{1 + \exp\left(\boldsymbol{\rho}_{w_{d,n}}^T \boldsymbol{\alpha}_{w_{d,n-l}}\right)}$$

Example

The first row of the table above would contribute the following elements to the loss function:

$$\Pr\left[\,\text{growth} \in \mathsf{C}(w_{d,n}) \mid w_{d,n} = \text{economic}\,\right] = \frac{\exp\left(\boldsymbol{\rho}^T_{\text{economic}}\boldsymbol{\alpha}_{\text{growth}}\right)}{1 + \exp\left(\boldsymbol{\rho}^T_{\text{economic}}\boldsymbol{\alpha}_{\text{growth}}\right)}$$

$$\Pr\left[\,\text{down} \notin \mathsf{C}(w_{d,n}) \mid w_{d,n} = \text{economic}\,\right] = \frac{1}{1 + \exp\left(\boldsymbol{\rho}^T_{\text{economic}}\boldsymbol{\alpha}_{\text{down}}\right)}$$

Loss function multiplies all such probabilities together and optimizes using gradient methods.

How Close are Words?

The standard way of judging whether word vectors are "close" is cosine similarity.

$$CS(i,j) = \frac{\boldsymbol{\rho}_i \cdot \boldsymbol{\rho}_j}{\|\boldsymbol{\rho}_i\| \, \|\boldsymbol{\rho}_j\|}$$

Measures whether vectors point in the same direction.

Terms Close to Uncertainty in FOMC Transcripts

term	sim
uncertainties	0.741
anxiety	0.48
pessimism	0.479
skepticism	0.465
optimism	0.445
caution	0.442
gloom	0.437
uncertain	0.433
sensitivity	0.427
angst	0.426

term	sim
challenges	0.415
fragility	0.405
clarity	0.401
concerns	0.4
risks	0.397
disagreement	0.387
volatility	0.384
tension	0.383
certainty	0.382
skepticism	0.38

Terms Close to Risk

term	sim
risks	0.737
threat	0.609
danger	0.541
dangers	0.463
vulnerability	0.457
chances	0.451
breakout	0.433
probability	0.426
possibility	0.409
likelihood	0.406

term	sim
misdirected	0.385
odds	0.379
uncertainty	0.375
concern	0.371
prospect	0.37
instability	0.363
potentially	0.352
concerns	0.352
challenges	0.346
risking	0.342

Document Similarity

Typical way of representing documents given a word embedding model is the average embedding for all words in document:

$$\boldsymbol{\rho}_d = \frac{1}{N_d} \sum_n \boldsymbol{\rho}_{w_{d,n}}$$

These representations can then be used to compute cosine similarity:

1. [Hansen et al., 2021] measures skill content of executive job postings.
2. [Gennaro and Ash, 2022] measures tone of political speeches.
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NB: $\boldsymbol{\rho}_d$ is not sensitive to word order!

Other Contextual Data

Similar algorithms can be used to represent any data where context informs relatedness.

[Ruiz et al., 2020] use embeddings to represent products: two products are similar when they appear in similar baskets.

Analogous idea for supply chains: firms are similar when they share similar co-suppliers.

Outline

Word Prediction in Large Language Models

To simplify notation, consider sequence of words $\mathbf{w} = (w_1, \ldots, w_N)$.

The prediction target of autoregressive or generative language models (e.g., GPT family) is $w_N \mid \mathbf{w}_{-N}$.

In bidirectional models (e.g., BERT), the prediction target is $w_n \mid \mathbf{w}_{-n}$.

In both cases, the prediction is informed by surrounding context.

Example of Next-Word Prediction Problem

After a season of positive corporate earnings announcements driven by AI adoption, NVIDIA's share price hit an all-time [MASK].

Which words are most likely to underlie [MASK]?

Two Alternative Examples with Six Words Removed

After a season of ~~positive~~ corporate earnings announcements driven by ~~AI~~ adoption, ~~NVIDIA's~~ ~~share~~ ~~price~~ hit an ~~all-time~~ [MASK].

After ~~a~~ ~~season~~ ~~of~~ positive corporate earnings ~~announcements~~ driven by AI ~~adoption~~, NVIDIA's ~~share~~ price hit an all-time [MASK].

Formalizing the Prediction Problem

Endow the masked word n with an embedding vector $\boldsymbol{\rho}_n \in \mathbb{R}^K$.

$\boldsymbol{\rho}_n$ can used to fit a probability distribution over the V vocabulary terms that can populate the nth element of the sequence.

Multinomial regression / feedforward neural network with $\boldsymbol{\rho}_n$ as input.

How can $\boldsymbol{\rho}_n$ be built to reflect relevant part of the context?

Also important for construction to be computationally efficient.

Attention Weights

The basic idea of attention [Vaswani et al., 2017] is to define a weight $\alpha_{n,m}$ for each attended word n and context word m.

Normalized so that $\sum_m \alpha_{n,m} = 1$.

Attention weights highlight the relevant parts of the context surrounding each word.

Weights are estimated during neural network training to optimize the quality of word prediction tasks.

Parameterization of Attention

Let $\mathbf{W}_q \in \mathbb{R}^{R \times K}$ and $\mathbf{W}_k \in \mathbb{R}^{R \times K}$ be query and key weight matrices.

Steps to generate attention weight $\alpha_{n,m}$:

1. Form query vector $\mathbf{q}_n = \mathbf{W}_q \boldsymbol{\rho}_n$
2. Form key vector $\mathbf{k}_m = \mathbf{W}_k \boldsymbol{\rho}_m$
3. Compute score $\tilde{\alpha}_{n,m} = \frac{\mathbf{q}_n \cdot \mathbf{k}_m}{\sqrt{R}}$
4. $\alpha_{n,m} = \frac{\exp(\tilde{\alpha}_{n,m})}{\sum_{m'} \exp(\tilde{\alpha}_{n,m'})}$

Using Attention to Update Embeddings

Suppose we have an initial embedding representation $\boldsymbol{\rho}_n^{(i)}$ for word n.

Let $\mathbf{W}_v \in \mathbb{R}^{S \times K}$ be matrix of value weights.

Project embedding into value vector $\mathbf{v}_n^{(i)} = \mathbf{W}_v \boldsymbol{\rho}_n^{(i)}$.

We obtain a new representation for word n via

$$\boldsymbol{\rho}_n^{(i+1)} = \mathbf{W}_0 \sum_m \alpha_{n,m} \mathbf{v}_m^{(i)}$$

where $\mathbf{W}_0 \in \mathbb{R}^{K \times S}$.

Transformer Model

A Transformer model is a deep learning model that repeatedly applies attention operations to initial word embeddings.

Inside a single Transformer block, attention operations are applied multiple times in parallel via multi-head attention.

Each updated word embedding is then passed through a feedforward neural network to non-linearly transform it prior to entering the next Transformer block.

Initial Embeddings

Each word in the input sequence has an initial embedding vector that is the sum of two distinct embeddings:

1. An embedding for the vocabulary term.
2. A positional embedding that depends on the location of the word in the sequence.

These embeddings are additional estimated network parameters.

Given the estimated structure of the whole network, every input sequence can processed even if it was not seen in training data.

Summary of Structure of Large Language Model

1. Begin with input sequence $w_1, \ldots, w_N$.
2. Assign initial embeddings to each element of sequence.
3. Repeatedly perform the following operations:
   3.1 Linearly combine embeddings with attention weights.
   3.2 Non-linearly transform each embedding with feed-forward neural network.
4. Output final embeddings for each element of sequence.
5. Use final embeddings for language prediction problem.

Modeling Choices

While this basic pipeline describes nearly every LLM, there is variety in:

1. Prediction target (e.g. bidirectional vs. autoregressive)
2. Training data
3. Length of context window
4. Number of Transformer blocks
5. Dimensionality of embedding vectors

BERT

Important example is BERT (Bidirectional Encoding Representations from Transformers) [Devlin et al., 2019].

Trained on BooksCorpus (800M words) and English Wikipedia (2,500M words).

Masked language modeling. 15% of words randomly masked and given [MASK] token. [MASK] token embeddings built to successfully predict underlying word.

Original paper had next-sentence prediction but has since been dropped from loss function in extensions [Liu et al., 2019].

Base model has twelve layers, 768-dimensional embeddings, 110M parameters.

Which Corpus?

Much of traditional text-as-data analysis fits models on corpora drawn from domain of interest.

Large language models were first fit on generic corpora like Common Crawl, Wikipedia, or Google Books.

More recent iterations expand the training data (but details becoming more obscure).

Important to realize that the training data contains the knowledge that a model can encode.

Any biases in the training data can also be inherited by the model.

Example GPT-3 Output

Prompt GPT-3 [Brown et al., 2020] with `He was very [MASK]` and `She was very [MASK]`.

Table 6.1: Most Biased Descriptive Words in 175B Model

Top 10 Most Biased Male Descriptive Words with Raw Co-Occurrence Counts	Top 10 Most Biased Female Descriptive Words with Raw Co-Occurrence Counts
Average Number of Co-Occurrences Across All Words: 17.5	Average Number of Co-Occurrences Across All Words: 23.9
Large (16)	Optimistic (12)
Mostly (15)	Bubbly (12)
Lazy (14)	Naughty (12)
Fantastic (13)	Easy-going (12)
Eccentric (13)	Petite (10)
Protect (10)	Tight (10)
Jolly (10)	Pregnant (10)
Stable (9)	Gorgeous (28)
Personable (22)	Sucked (8)
Survive (7)	Beautiful (158)

Outline

Document Similarity

LLMs produce vector representations of word sequences which can be used in place of non-contextual methods.

Plausible argument for preferring bidirectional models, which exploit full structure of document.

LLMs can produce different vectors for

economic growth is weak but long-term productivity trends are strong
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Open question is to what extent this improves similarity measures.

Zero/Few-Shot Learning

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Formulate a sequence of words such as

> *"Consider the sentence 'the economy is booming'. Is the sentiment in this sentence positive, neutral, or negative?"*

This text is converted to $\mathbf{w} = (w_1, \ldots, w_N)$.

$N + 1$th word is drawn from $\Pr[\, w_{N+1} \mid \mathbf{w} \,]$.

$N + 2$th word is drawn from $\Pr[\, w_{N+2} \mid \mathbf{w}, w_{N+1} \,]$, and so forth.

Already by GPT-2 emergent zero-shot learning behavior observed from training on next-word prediction loss.

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See [Bybee, 2023] and [Hansen and Kazinnik, 2024] for early applications in economics.

Generating Structured Information

Even outside economic measurement, LLMs add value by mapping unstructured data into structured representations.

For example, extracting specific narratives from text, e.g. "who did what to whom."

LLMs largely overcome need for OCR conversion of images to text.

Very useful for fields like economic history.

Conclusion

Foundation LLMs are large-scale word prediction machines.

But word prediction machines can be surprisingly useful!

Lack of benchmarking on economic tasks makes quantifying value added to measurement a challenge.

For any given gain in measurement accuracy, need to trade off lack of transparency and reproducibility.

Deeper questions surrounding LLMs ability to learn realistic "world model" [Vafa et al., 2024].

As with word2vec, more general idea of embedding sequential data [Gabaix et al., 2023].

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