

From Pen to Print: Tracing the Evolution of Poverty Narratives in The Times Over Centuries

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Our aim & research questions

Explore the media narratives regarding the poverty issue in the newspapers.

- What topics discussed in the articles, and are there any time-varying changes over the time?
- Is there any association between “economic”-related topics and the financial market index?
- What is the overall political preference of the selected newspaper articles towards the different parties?



Data Source

- *The Times* newspapers discussing the poverty issue between 1785 to 2012,
- The University Library automatically converts PDF files into editable txt formats.
 - OCR: a value between 0 to 100



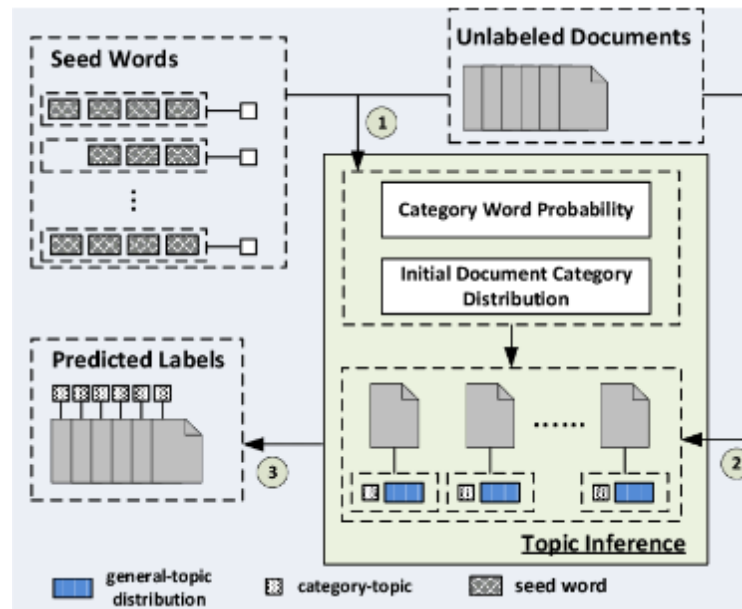
Methods

1. Seeded LDA

- a. Topic modelling
- b. Semi-supervised MLs

2. Advantages compared to LDA:

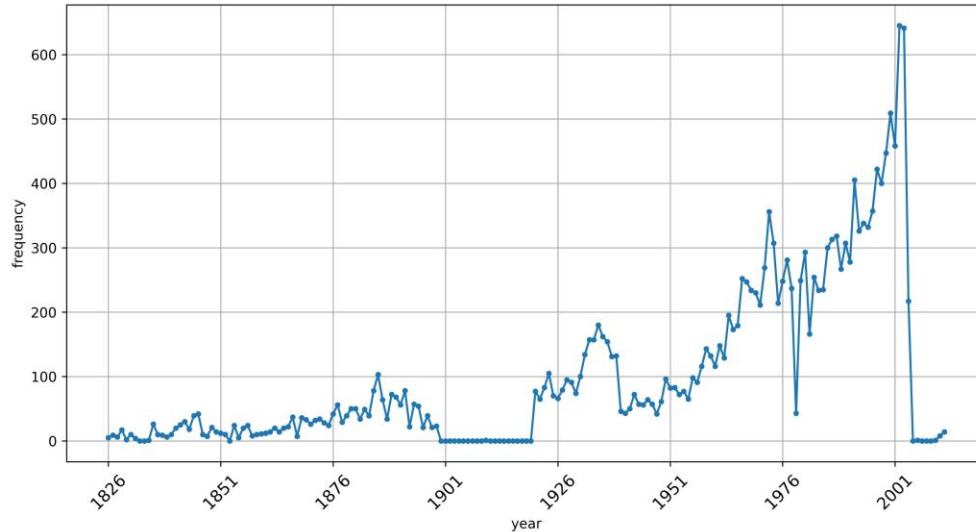
- a. Control topic numbers
- b. Incorporate target keywords
- c. Filter “noises”



Topics

1. Poor Relief
2. Workhouse Conditions
3. Unemployment
4. Child Poverty
5. Education and Poverty
6. Government Policies/Social Reform Movements
7. Poverty and Migration/War
8. Poverty and Crime/Drug/Alcohol

Time-Series Trends -- Overall

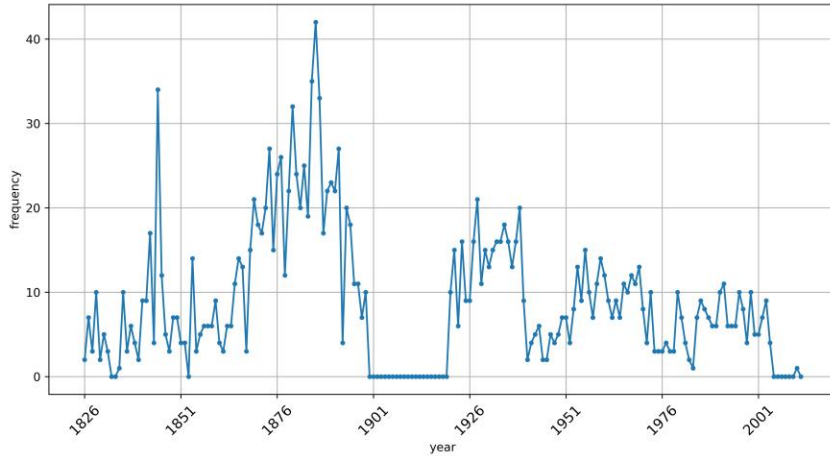


Note: articles are filtered with the OCR value above 80.

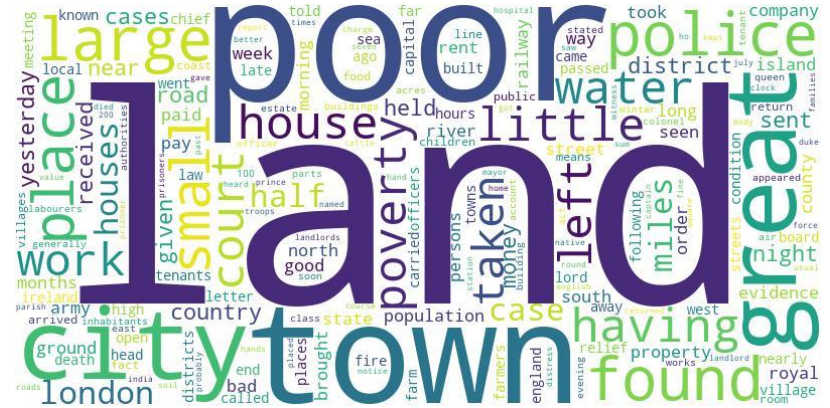
18,521 articles remain

| Year | Mean | Stdev | Min | 0.25 | 0.5 | 0.75 | Max |
|--------------------|------|-------|-----|------|-----|------|-----|
| Number of Articles | 116 | 130 | 1 | 23 | 64 | 168 | 645 |

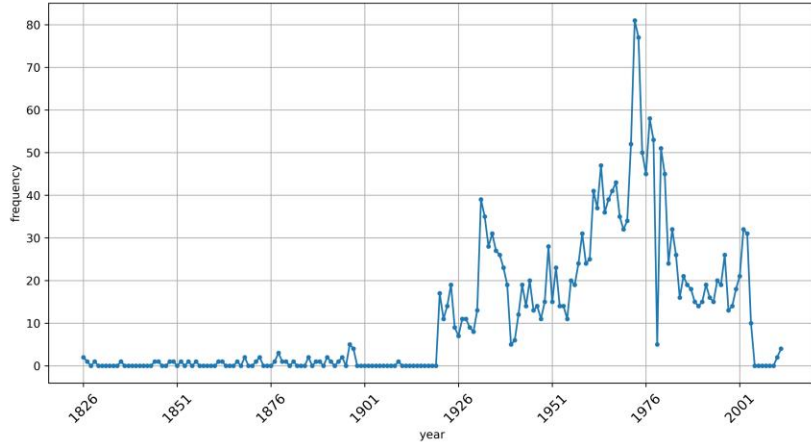
Workhouse Conditions



Note: articles are filtered with the OCR value above 80.
unrecognised words are also filtered out.

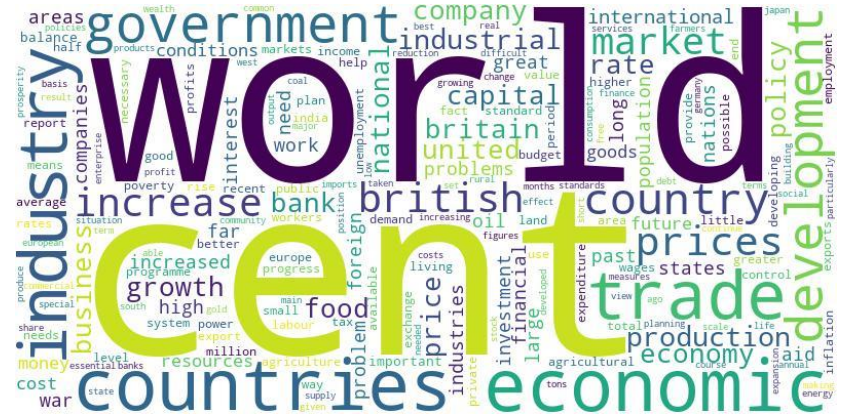


Unemployment



Note: articles are filtered with the OCR value above 80.
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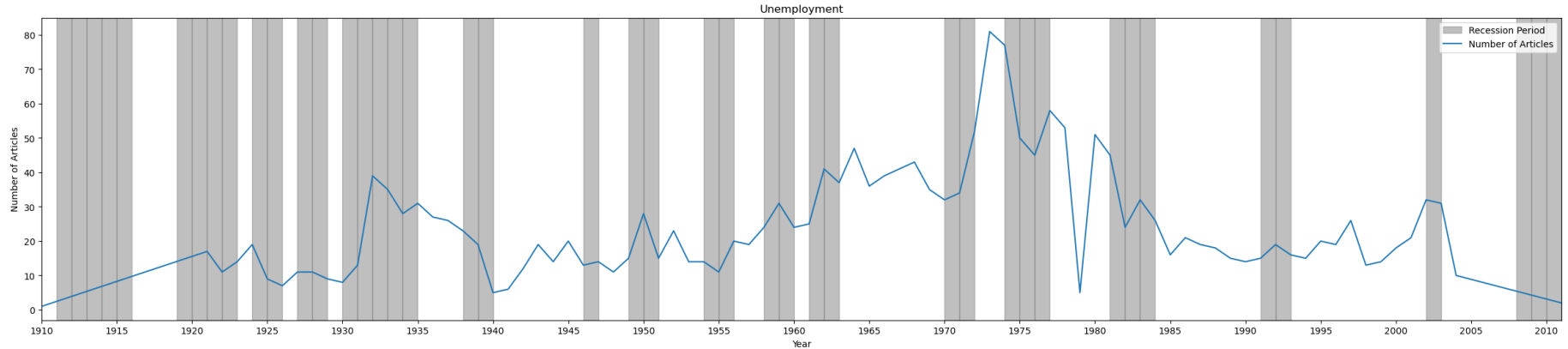


Proportion of topics in different periods

| Topic \ Percentage (%) | Total | 19th | 20th |
|---|-------|------|------|
| Education and Poverty | 18.3 | 1.3 | 17.3 |
| Child Poverty | 18.3 | 0.4 | 20.6 |
| Poverty and War/Migration | 15.5 | #N/A | 17.0 |
| Poverty and Crime/Drug/Alcohol | 12.3 | 36.8 | 10.5 |
| Unemployment | 11.6 | 2.3 | 14.1 |
| Workhouse Conditions | 8.9 | 46.0 | 5.0 |
| Government Policies/Social Reform Movements | 8.1 | 12.9 | 8.7 |
| Poor Relief/Poverty Alleviation | 7 | 0.1 | 6.9 |

- “Workhouse Conditions” articles were the top-ranked topics in 19 century, but were down to the bottom one in 20 century.
- “Unemployment” articles were covered less in the early period whereas they were frequently appeared in the 20 century.
 - it was recognized as one of the main structural factors linking to poverty.
- Other topics such as “Education and Poverty”, “Child Poverty”, as well as “Poor Relief” also exhibit an increasing trend over the time.

Unemployment and Recession



- There is a virtually high association between NBER-dated recession period and the number of “unemployment” news articles.
- For example, the Great Depression (1929–1939) was overlapped with the high media counts.

Determinants of “unemployment” narratives

$$News_t = \alpha + \beta_1 Recession_t + \beta_2 Ret_t + \beta_3 Ret_{t-1,t-12} + \beta_4 Vol_t + Time + \varepsilon_t$$

- Where $News_t$ is the number of newspaper coverage regarding “unemployment” in year-month t .
- $Recession_t$ is a dummy variable of 1 if the year-month t is a NBER-dated recession period.
- Ret_t is the monthly return in month t .
- $Ret_{t-1,t-12}$ is the past 12-month cumulative return.
- Vol_t is the past 12-month return volatility.
- $Time$ is the year fixed effects.

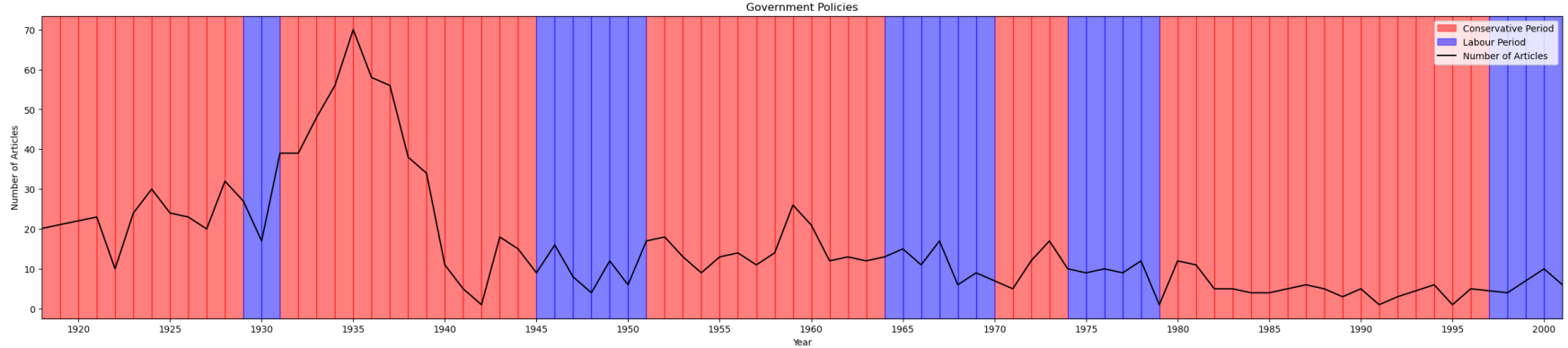
Determinants of “unemployment” narratives

| | (1) | (2) |
|--------------------|--------------------|----------------------|
| | Unemply news | Total news |
| Ret_t | 0.903 (1.14) | 1.014 (0.25) |
| Ret_t-1,t-12 | 0.9200** (2.31) | 1.9902 (0.97) |
| Vol | 1.918 (1.35) | -6.6648 (-0.92) |
| Recession | 0.1641 (1.38) | -0.1642 (-0.27) |
| _cons | 0.7949*** (4.3) | 20.6284*** (21.7) |
| R-squared | 0.5832 | 0.8281 |
| N. of Obs. | 1799 | 1799 |
| Year Fixed Effects | Yes | Yes |

t statistics in parentheses = " * p<0.10; ** p<0.05

- The number of “unemployment” articles is positively associated with the past 12-month cumulative return of UK equity index.
- In contrast, we do not observe such an association between the total Times newspapers and the past return performance of the equity index.
- This suggests that journalists’ coverage of economic-related topics largely depends on macroeconomic conditions.

“Government policies” and Political Parities



- We do not observe any significant difference between Labour and Conservative Party in terms of “government policies” news articles.
- The spike of media counts in the early sample period appears to be related to the Great Depression (1929–1939).

“Government Policies” and Political Parities

$$SentScore_t = \alpha + \beta_1 Conservative_t + \beta_2 Recession_t + \varepsilon_t$$

- Where $SentScore_t$ is the aggregated sentiment score at a year-month t .
- $Conservative_t$ is a dummy variable of 1 if the Conservative party represents the government.
- $Recession_t$ is a dummy variable of 1 if the year-month t is a NBER-dated recession period.

| | (1) | (2) |
|---------------------|----------------------|------------------------|
| | HIV4 | LM2011 |
| Recession | 0.0409*** (2.62) | 0.0185 (0.72) |
| Conservative | 0.0149 (0.97) | 0.0172 (0.68) |
| _cons | 0.2608*** (19.46) | -0.4308*** (-19.55) |
| R-squared | 0.0151 | 0.002 |
| N. of Obs. | 546 | 546 |
| _Year Fixed Effects | No | No |

Follow-ups

- Due to poor printing quality, the early sample texts tend to contain many unrecognised English words even though the OCR value indicates a high conversion rate.

- An example:

I wouldnotba iqwita him to conne to my house

- ChatGPT predicts the original sentence is likely to be:

I wouldn't invite him to come to my house.

- A large number of such recognised English words have critically affected the accuracy of textual analysis. Many keywords which should be in the NLP corpus have to be filtered out.
- This, as a result, leads to an inaccurate topic modelling as well as sentiment analysis outcomes.
- Large language models are likely to correct such texts. This will need further fundings to support massive usage.