以法說會逐字稿
預測半導體產業前景

研究流程

數據蒐集─
費半30歷史企業

數據處理─
詞性還原、斷詞

自編
市值加權指數

市場狀態分類─
Good/Bad/Neutral

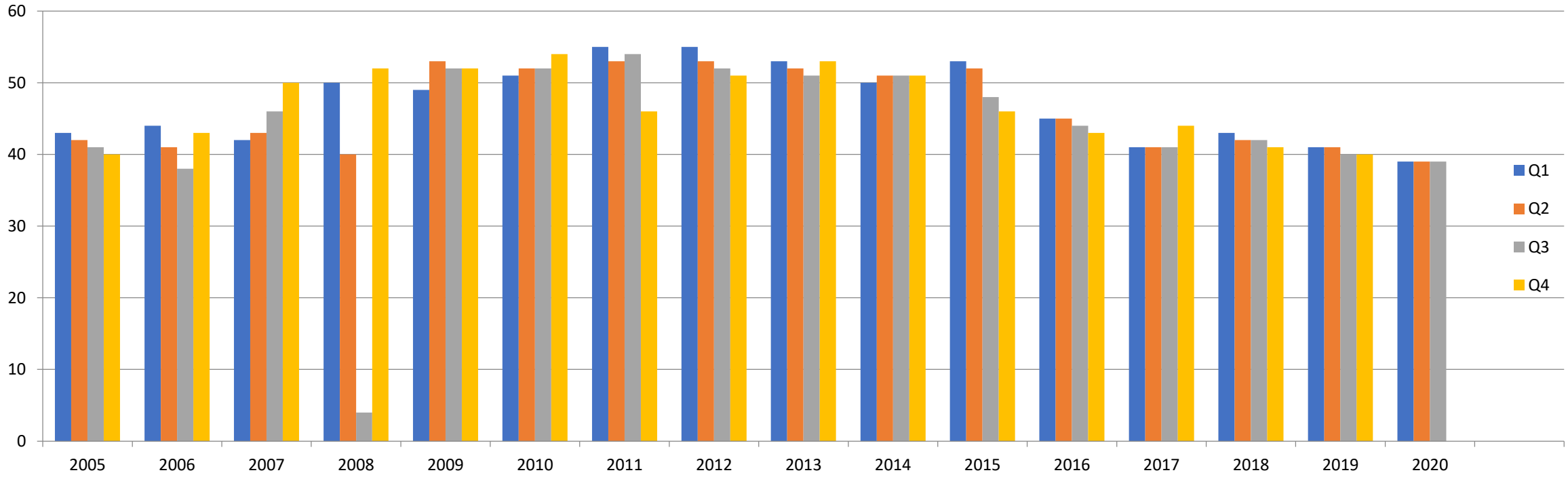
統計檢定─
將詞按照市場狀況分類

建構機器學習預測模型

半導體產業
前景預測

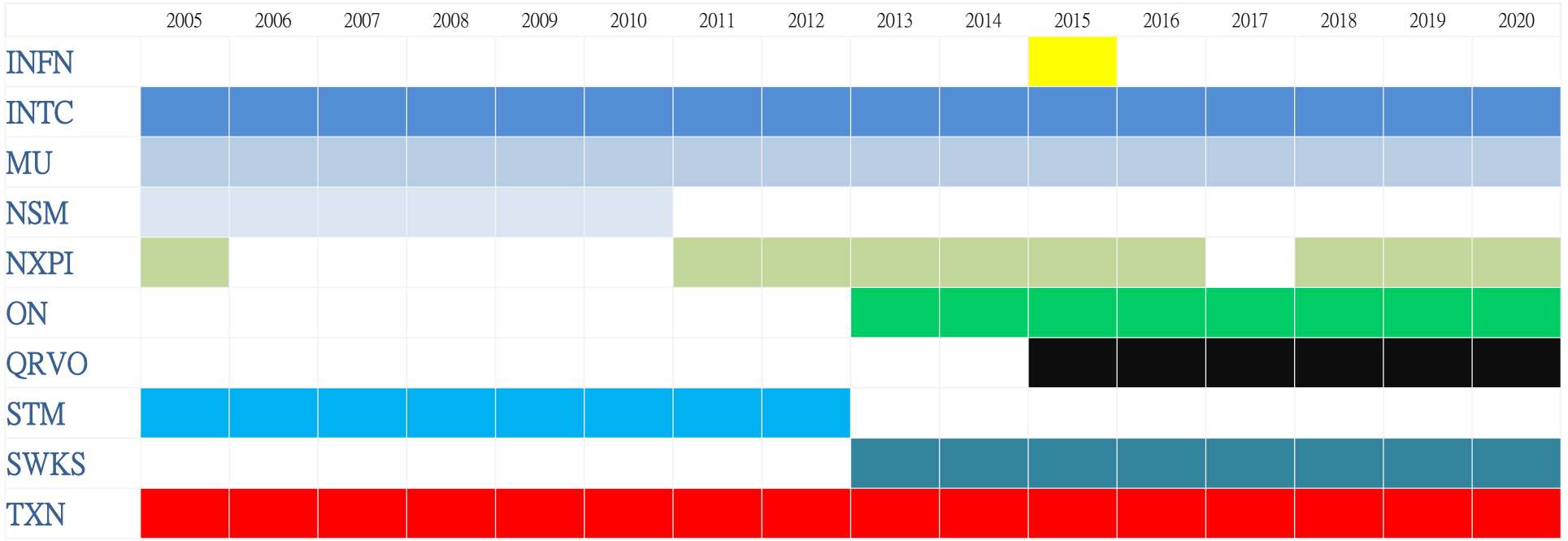
資料 – 歷史費半企業

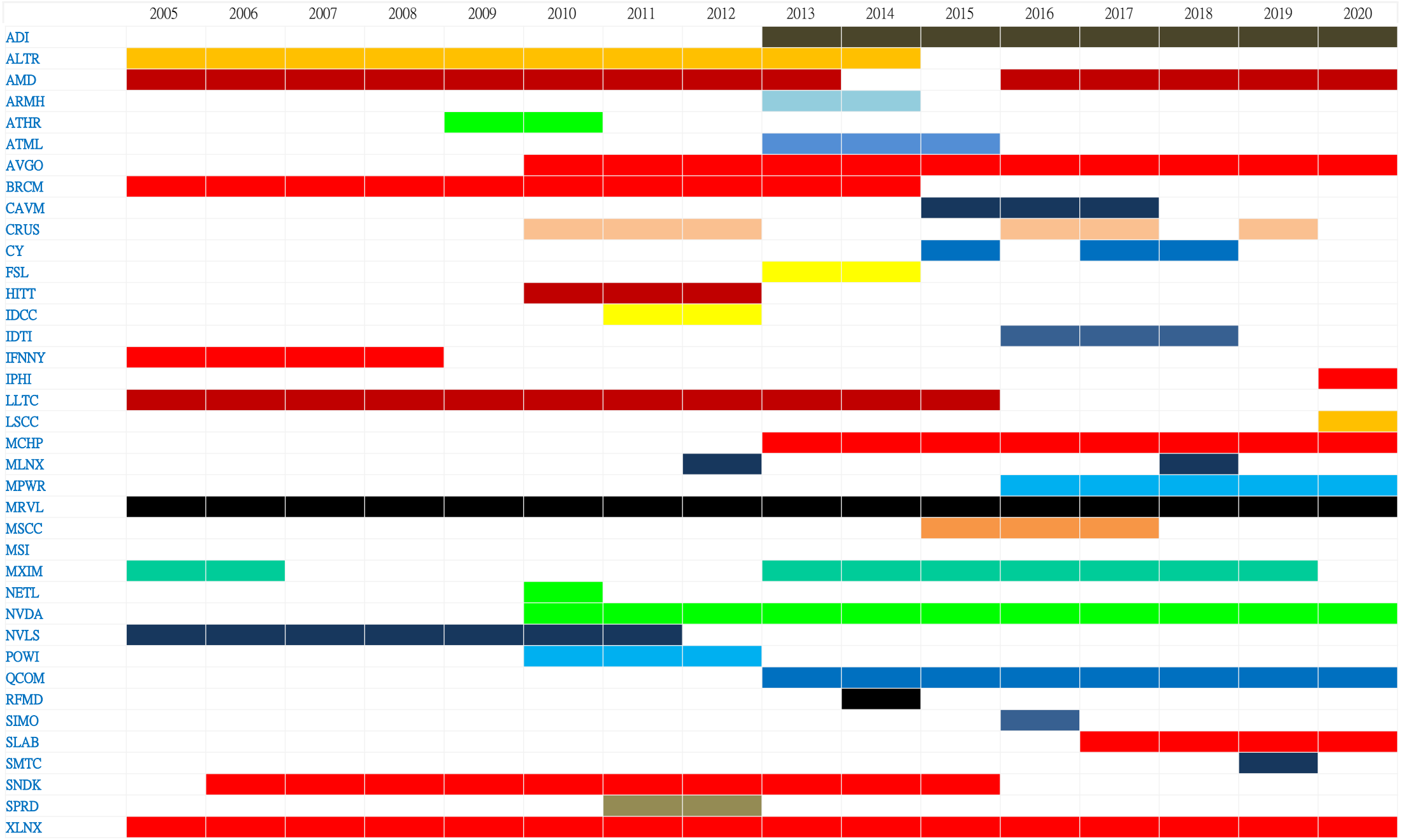
- 期間：2005/Q3 – 2020/Q3
- 總公司數：63
- 總文本數：2810



資料 – 歷史費半企業

- 上游：48
- 中游：14
- 下游：1

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RFMD
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SLAB
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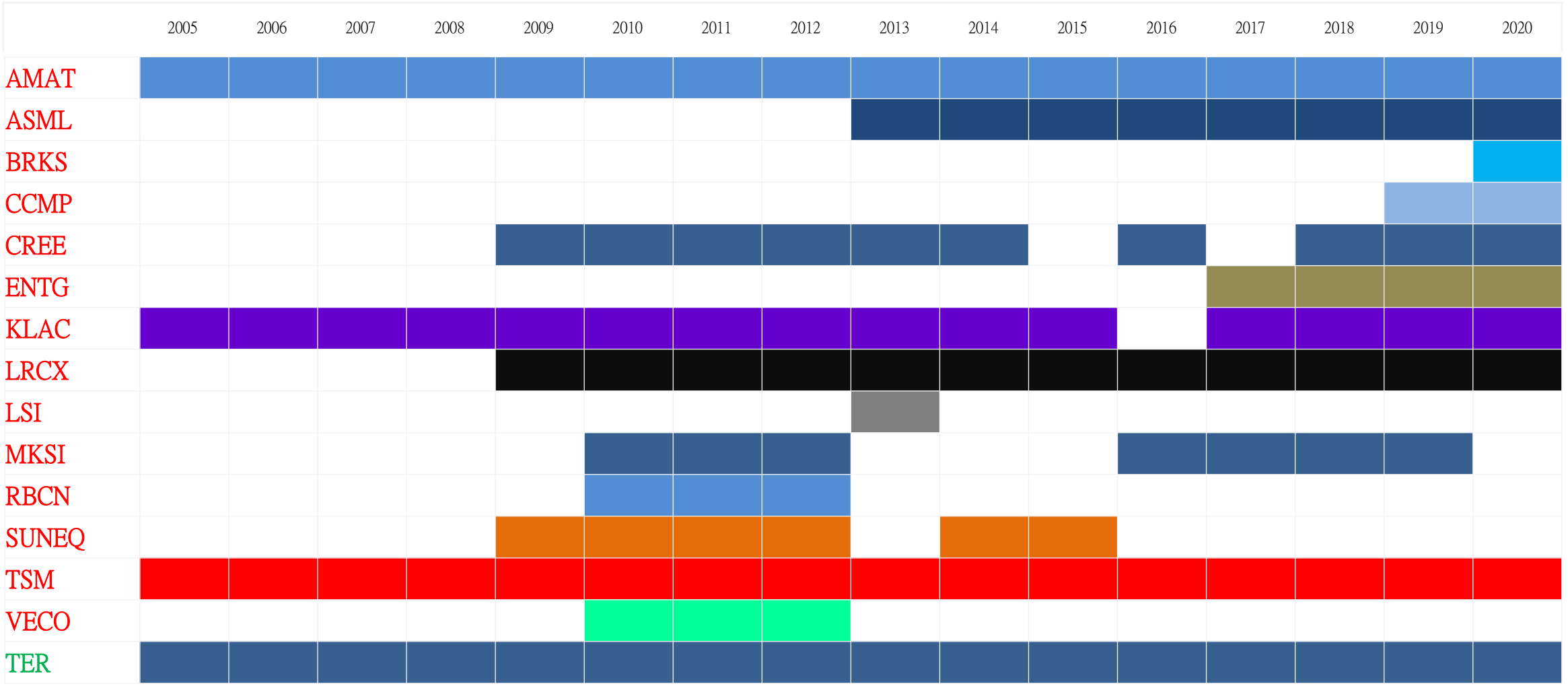
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數據處理—詞性還原(Lemmatization)

英文單字會因時態、單複數不同而變化，若不處理會造成文字探勘研究的偏誤，例如 the performance looks good 和 the performance is better than last year 兩句話的 good 和 better 是比較級關係，卻會被當成兩個不同的單字

- 使用套件：NLTK + Stanza(美國 Stanford大學開發之語言處理套件)
  - 以 it’ s better than before 為例
  - NLTK: it ‘s good than before
  - Stanza: it be better than before
- Stanza 無法處理形容詞之詞性還原、NLTK不夠細緻，縮寫(ex. 無法處理 It ‘s)
- 目標：

went/ goes → go
cars → car
better → good

數據處理–斷詞(Segmentation)

先進行各種文本預處理，例如透過人工標記的方式保留完整片語、去除符號及stop words，使研究更精確

- 使用套件：NLTK
- 斷詞預處理：去除符號及stopwords 後，在保留片語的前提下將句子斷成單詞
- 以 However, there are a lot of companies doing this!為例

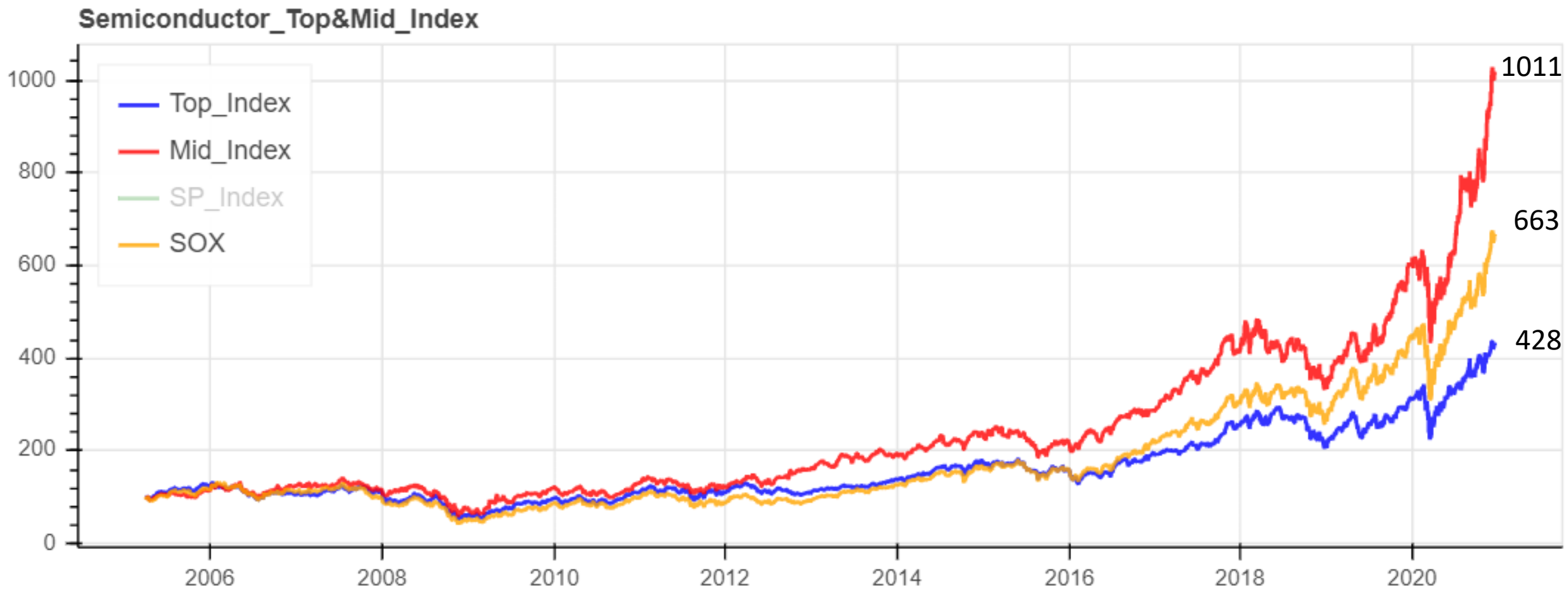
處理順序

  - 詞性還原後的句子: however, there be a lot of company do this!
  - 去除符號及 stopwords：however there a lot of company do this
  - 保留片語進行斷詞： however, there, a lot of, company, do, this
  - 若不保留片語語意會不精準：however, there, a, lot, of, company, do, this → 得到一串詞的 list 以進行後續分析

- Stop words 定義(Stanford)：some extremely common words which would appear to be of little value in helping select documents matching a user need are excluded from the vocabulary entirely. These words are called *stop words* .

自編市值加權指數

將半導體公司區分為上游、中游，並以建立景氣指數，用以後續判斷state



市場狀態分類—Good/Neutral/Bad

以自編加權指數作為判斷依據，依照報酬的分配區分為三個不同的狀態，分配前25%視作Good狀態，中間50%視作Neutral狀態，後25%視作Bad狀態

- 上游State結果

quarter	state
Q3_05	good
Q4_05	neutral
Q1_06	neutral
Q2_06	bad
Q3_06	neutral
Q4_06	bad
Q1_07	bad
Q2_07	good
Q3_07	neutral
Q4_07	bad

- 中游State結果

quarter	state
Q3_05	neutral
Q4_05	neutral
Q1_06	neutral
Q2_06	bad
Q3_06	neutral
Q4_06	neutral
Q1_07	neutral
Q2_07	neutral
Q3_07	neutral
Q4_07	bad

市場狀態結果—Good/Neutral/Bad

經過t-test篩選之後，將具統計顯著的詞過濾出來，再判斷詞是否在某個state時與其他state有遞減或遞增的關係，同時滿足這兩個條件，才能夠作為有意義的詞

```
t1,p1 ,t2,p2= check_words_t_test_result('growth')
print(f'good bad t-value :{t1}')
print(f'good bad p-value :{p1}')
print(f'good neu t-value :{t2}')
print(f'good neu p-value :{p2}')
```

```
<ipython-input-5-8c3172c7f9e5>:16: FutureWarning:
will perform elementwise comparison
  index = np.argwhere(words == keyword)
```

```
good mean freq :0.0035780872088622346
bad mean freq :0.0037920120814475934
neutral mean freq :0.00432032226175882
good bad t-value :-1.6045103547971702
good bad p-value :0.10860786452656342
good neu t-value :-5.722513564604276
good neu p-value :1.0538800254848262e-08
```

```
t1,p1 ,t2,p2= check_words_t_test_result('business')
print(f'good bad t-value :{t1}')
print(f'good bad p-value :{p1}')
print(f'good neu t-value :{t2}')
print(f'good neu p-value :{p2}')
```

```
<ipython-input-5-8c3172c7f9e5>:16: FutureWarning: ele
will perform elementwise comparison
  index = np.argwhere(words == keyword)
```

```
good mean freq :0.0053045445417035245
bad mean freq :0.006199974587582467
neutral mean freq :0.005744301231630468 5
good bad t-value :-4.840397604210667
good bad p-value :1.2996223000160013e-06
good neu t-value :-2.854071068585927
good neu p-value :0.004317558789745016
```

1st time BERT model (base-cased)

- 總樣本數: 98965 (pos:25747, neu:46618, neg:26601)
- 訓練集: 69276(pos:7724, neu:13986, neg:7980)
- 樣本外:pos: 20/83, neu: 44/136, neg: 61/81

改進流程

- 嘗試使用其他預訓練模型(XLNet、ELECTRA.....)
- 將State 分法修正，依照個別公司股價表現進行標註
- 取完顯著字詞後進行產業內專業字詞篩選
- 嘗試其他預測方式(Dictionary based等)