

Fine-grained implicit sentiment processing of polar economic events

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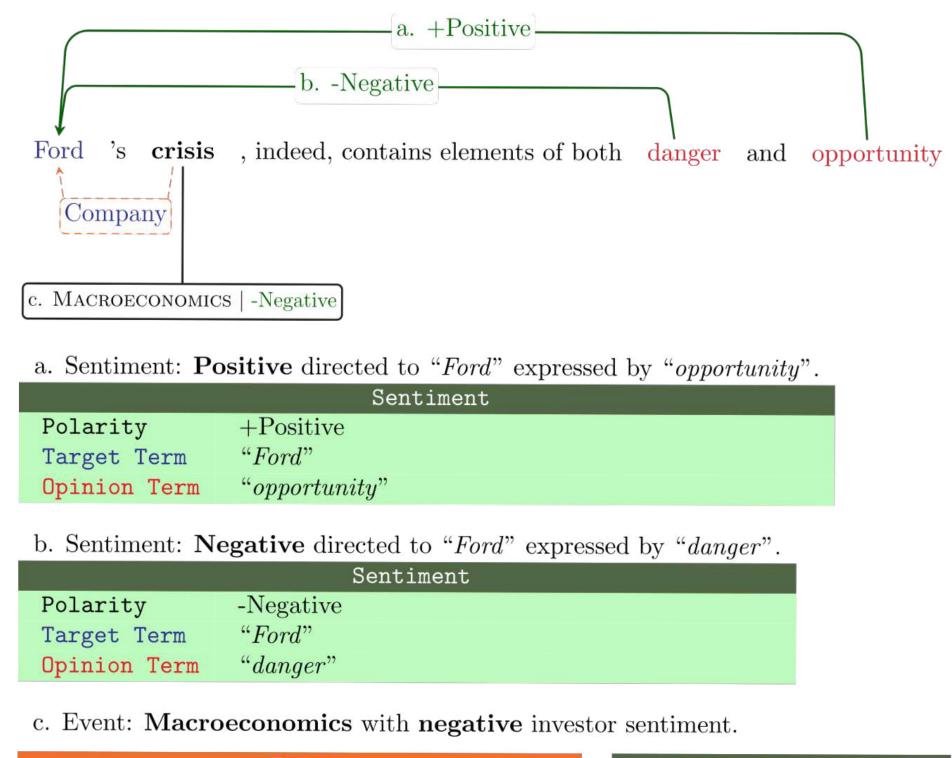
- Feasibility check: given gold polar facts classify implicit sentiment?
- Model selection: Hyperband hyperparameter search. [4] Model eval.: Train-dev-test + McNemar's significance test.
- Fine-tune several transformers including several in-domain.
- Add lexicon scores from general domain and finance at clf head.

Holdout results. Precision (P), recall (R), F_1 -score (F_1) percentages are macro-averaged. Accuracy (A) with the p-value of McNemar's test w.r.t. best on dev RoBERTa $_{Large}$ +econ+general.

test w.i.t. best on dev Robert la $Large$ reconfigencial.									
model w lexicons	Р	R	F1	A	р				
$BERT_{Base}$	57.3	55.4	54.6	68.3	3.6e-10***				
+ econ.	62.8	<u>59.0</u>	<u>58.5</u>	<u>71.3</u>	5.6e-05***				
+ econ.+general	59.8	57.9	57.3	71.2	3.3e-05***				
FinBERT-SST $_{Base}$ [5]	60.8	56.2	56.3	71.2	2.7e-05***				
+ econ.	<u>72.2</u>	54.0	52.5	73.2	7.1e-03**				
+ econ.+general	63.0	<u>57.9</u>	<u>58.4</u>	<u>73.3</u>	2.2e-02*				
DeBERTa $_{Base}$ [6]	59.5	<u>58.4</u>	57.9	71.6	7.8e-05***				
+ econ.	62.7	57.7	57.7	72.5	1.3e-07***				
+ econ.+general	<u>70.4</u>	58.2	<u>58.9</u>	<u>74.9</u>	1.3e-03**				
RoBERTa $_{Base}$ [7]	58.4	55.9	54.0	74.5	1.2e-01				
+ econ.	63.8	61.5	61.5	74.4	1.4e-01				
+ econ.+general	63.5	<u>62.6</u>	<u>62.8</u>	<u>75.0</u>	2.4e-01				
$BERT_{Large}$	58.8	56.2	56.0	73.2	9.5e-03**				
+ econ.	61.8	<u>61.6</u>	<u>61.5</u>	72.8	4.3e-03**				
+ econ.+general	<u>62.0</u>	58.0	58.1	<u>74.0</u>	5.5e-02				
RoBERTa $_{Large}$ [7]	<u>65.8</u>	<u>63.0</u>	<u>63.2</u>	<u>77.5</u>	1.1e-01				
+ econ.	63.8	62.6	63.0	75.4	5.8e-01				
+ econ.+general	61.9	58.8	58.3	75.9	-				

- Adding lexicon helps marginally: †P but overfit
- RoBERTa is robust, base > many large.
- → 78% Accuracy: polar fact polarity classification is hard but feasible.

- SENTIVENT Representation 286 economic news articles annotated with: ACE/ERE event structures + target-sentiment expressions. \rightarrow 9500 target + opinions [1, 2]
 - Polar facts: connotational implicit sentiment of events, facts [3] → challenge in SA
 - Combine events + sentiment for targeted polar fact processing: event participants = targets.
 - Applications: market analysis, trading strats, event studies



Investor sentiment:

"Implicit and explicit text that expresses or affects an investor's attitude towards an economic actor."

Bullish 🙀 Bearish 🐷 Neutral =



 Fine-grained token-level: Target-opinion-polarity triplet extraction

(Ford's share price, weakness, NEG) (Ford's share price, surpass, NEG) (Tesla, surpass, POS)

 Apply end-to-end SotA model "Grid Tagging Scheme for ABSA" (GTS) [9]

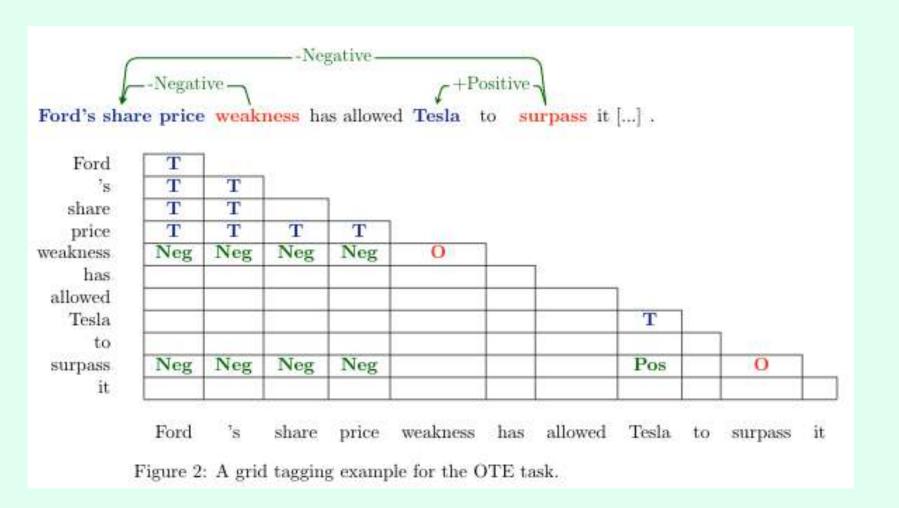


Table 1: Precision (P), Recall (R), and F_1 -scores on Opinion term (sentiment token span) extraction, Aspect term (target token span), and combined Triplet extraction (opinion term, aspect term, sentiment polarity).

Dataset + Model	Aspect term		Opinion term			Triplet			
	Р	R	F_1	Р	R	F_1	Р	R	F_1
SENTiVENT Roberta $_{Base}$ [7]	57.9	60.6	59.2	41.3	39.12	40.2	26.4	20.8	23.2
SENTiVENT Roberta $_{Large}$ [7]	59.0	57.7	58.4	43.6	39.0	41.2	24.4	19.2	21.5
SENTIVENT FinRoBERTa $_{Base}$ [8]	31.2	44.1	36.5	20.2	24.5	22.1	8.6	8.1	8.3
Reviews [11] Roberta $_{Base}$ [7]	85.8	88.0	86.9	87.6	88.0	87.8	75.0	74.1	74.5
Reviews [11] Roberta $_{Large}$ [7]	84.7	89.3	86.9	86.6	88.3	87.5	74.8	74.4	74.6

Clause

(Revenue.Increase@12-14)

"American Airlines"

"crisis"

Participant & Filler Arguments

 Realistic task: classify polar <u>clauses</u>: OpenIE clause extractor + dependency rule fall-back to split original sentences in clauses:

Trigger

Subtype

Modality

Negation

"Passenger count PAX grew 0.8 %, while it declined 0.7 % on a year-to-date basis ."

- \rightarrow [W NEG] "it declined 0.7 % on a year-to-date basis." → [POS] "passenger count PAX grew 0.8 %,"
- → 57% macro-F1, 66% Acc for RoBERTa
- Adding lexicons ↑P, ↓R
- Confusion "none" vs "neutral".

model w lexicons	Р	R	F1	А	p
FinBERT-SST $_{Base}$ [5]	<u>53.7</u>	53.9	52.2	60.0	< .001***
+ econ.	53.6	<u>54.8</u>	<u>53.4</u>	60.2	< .001***
+ econ.+general	52.5	53.1	52.0	<u>60.4</u>	< .001***
$BERT_{Large}$	54.8	55.8	54.6	62.0	.018*
+ econ.	<u>56.4</u>	<u>57.1</u>	<u>55.6</u>	<u>62.8</u>	.086
+ econ.+general	55.1	52.3	50.3	61.3	.002**
DeBERTa $_{Base}$ [6]	53.8	53.7	52.5	63.3	.214
+ econ.	<u>56.7</u>	<u>56.0</u>	<u>55.2</u>	63.7	.34
+ econ.+general	52.9	52.4	50.1	<u>64.0</u>	.493
RoBERTa $_{Base}$ [7]	<u>57.8</u>	55.3	55.1	<u>66.2</u>	.26
+ econ.	56.2	<u>56.6</u>	<u>55.7</u>	63.7	.373
+ econ.+general	57.6	56.0	54.2	65.5	.541
RoBERTa $_{Large}$ [7]	56.7	<u>57.8</u>	56.7	<u>64.8</u>	.944
+ econ.	<u>59.1</u>	57.6	<u>56.8</u>	64.8	-
+ econ.+general	56.0	55.6	54.6	63.5	.232

Sentiment-on-event

Opinion term "crisis"

Polarity

Target term

Holdout results for clause-based implicit polar fact classification. Precision (P), recall (R), F_1 -score (F_1) percentages are macro-averaged. Accuracy (A) with the p-value of McNemar's significance w.r.t. best dev (RoBERTa $_{Large}$ +econ.).

- Implicit much harder than explicit:
 - "Closed" economic domain?
 - Beyond lexical methods
 - Polar facts remain a challenge.
 - → SENTiVENT ideal resource for pushing polar fact processing





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