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IPS 243
An Alternative Approach for Getting Investment Direction with the Combination of Unstructured and Structured Data

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The views expressed here are those of the authors and do not necessarily reflect the views of Bank Indonesia

OUTLINE

BACKGROUND AND GOALS

BACKGROUND

- **Investment is one of the main indicators to measure state of the economy in Indonesia** (30%, in Indonesia's GDP). However, GDP and Investment are published and available on a quarterly basis with a publication lag of one month.
- Bank Indonesia provides large value payment system, RTGS (Real Time Gross Settlement), that can **generate data related to fund transfers, including investment transactions**.
- Previous research has shown evidence that **investment decision** influenced by sentiment data from newspaper and social media.
- Advancements of technology have opened the **opportunity to explore large dataset of payment data as structured data and news data as unstructured data for monitoring economic activity**.

GOALS

Combining information from unstructured data (news) **and** high frequency **structured data** (large value payment system) **as an alternative approach for investment direction** in Indonesia, by utilizing Big Data Analytics methodology, particularly text mining.

DATA SOURCE

UNSTRUCTURED

- **News Data from 30 prominent newspaper that curated by Bank Indonesia from 2017 – now.**
- **Average total articles are 850 articles/day ≅ 27.000 articles/month**

STRUCTURED

Data Source : BI-RTGS Transactional Data

Transaction Type : Banks' transactions o/b of customer (TTC 100 & 101) ~ MT103

Total Transactions : ≅ 800.000 transactions/months (out of 1,2 mio transactions)

Settlement Time	Transaction Type Code (TTC)	Sender Bank	Receiver Bank	Nominal	Block4
Transaction settlement time (MM/DD/YYYY HH:mm)	**RTGS transaction code** **100 :** Transaction o/b of customer **101 :** Transaction o/b of customer (w/o account) **111 :** Forex Buy/Sell **112 :** Interbank Money Msrket **etc.**	**Sender's Bank SWIFT Code (BIC)** e.g.: CENAIDJA	**Receiver's Bank SWIFT Code (BIC)** e.g.: BMRIIDJA	Transaction amount in Rupiah	Transaction message, sent by Sender Bank into BI-RTGS system

Settlement Time	TTC	Sender Bank	Receiver Bank	Nominal	Block4
5/2/2018 13:35	100	DXXXIDJA	MXXXIDJA	xx,x0,000,000.00	:20:02RE2018043XXXXX#:23B:CRED#:23E:SDVA#:32A:180502IDRxxx0000000,00# :50K:XYZ JAYA,PT#JL. JEND GATOT SUBROTO KAV 51-52#10270 JAKARTA PUSAT#INDONESIA#:52D:BANK DXXX JAKARTA INDONESIA# :53A:/D/521067000990#DXXXIDJA#:57A:/C/520008000990#MXXXIDJA# :59:/121000XXXXXXX#UVW ALIH DAYA, PT# :70:INV. 1804-0167#R/LOCAL# :71A:OUR#:72:/CODTYPTR/100#/CLRC/0670304#:77B:/FEAB/R /PTR/LOCAL

METHODOLOGY

Unstructured Data: News -- *(as the **leading** indicator)*

Text pre-processing → Bag of words → Tfidf feature extraction → Feature vector → Model training & evaluation → model

Filtered, Annotated Data

1 Model Preparation Stage

Full Database

Filtering → Text pre-processing → Bag of words → Tfidf feature extraction → Feature vector → classification → Inferred data → Index construction

Filtered Data

2 Inference on full data & index construction stage

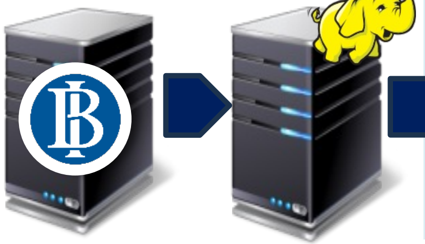
Pos, neg, (sector, foreign/domestic)

3 Validation & analysis stage

Structured Data: RTGS -- *(as the **prompt** indicator)*

1 Data Preparation Stage

BI-RTGS → Hadoop



2 Transaction Data Analysis Stage

Parsing: Extract the field sender, receiver, and transaction description

Entity resolution: Identify the unique entity. Potentially different writing form

Classification: Segmentation/classification of the transactions with text mining.

Aggregation: Summarise the identified transactions

3 Validation & analysis stage

METHODOLOGY UNSTRUCTURED DATA

Model Preparation

- **Filtering:** Filter out non-Indonesian language news**,** tokenize the news into sentences and filter the sentences that contain any keywords that may be related to investment.
- **Data annotation (for model training):** For the model training purpose, we annotate the filtered data. We obtain 1200 positive (+1) and 873 negative or not related (-1). Examples:

menurutnya, ketertarikan grup asal Jepang untuk melakukan investasi di sejumlah proyek energi menunjukkan iklim investasi di indonesia sangat baik. *(**In English:** according to them, the enthusiasm of a group from Japan to invest on some energy projects shows that the investment climate in Indonesia is very good)*	**Positive (+1)**
para investor tidak tertarik lagi melakukan eksplorasi, sehingga produksi minyak nasional akan terus turun. *(**in English**: the inverstors are no longer interested in doing exploration so that the national oil production will continue to decrease)*	**Negative (-1)**

<u>Annotated Data's wordcloud:</u>

Positive (in English): will, able, stock, fund, etc..

Negative (in English): will not, risky, crisis, etc.,

- **Text Preprocessing:** Case folding, remove punctuation and digit, remove stopwords, tokenize into words
- **Feature Extraction:** tfIdf weighting $tfidf_w = tf_w \, * \, \frac{N}{df_w}$

METHODOLOGY UNSTRUCTURED DATA

Inference Model for Sentiment Classification

- Our task is a very **domain specific**. If leveraging anyway any pretrained LLM such as IndoBERT can potentially be misleading. e.g.:

  Tarif pajak yang turun memberikan pengaruh bagi iklim investasi
  *(**in English**: the decrease of tax rate gives impact into the investment climate)*

  Generally, "turun" (decrease) is a sign of negative sentiment. In our case, the decrease of the tax rate is a positive sign of investment sentiment. Thus, we need to do some customizations for our domain.

- **Data annotation can be expensive**! But naturally, we have prior knowledge √ →may be elaborated for the inference
- **Some methods may be limited**: on learning and/or inference only on specific model e.g. (Schapire, 2002) Boosting/Logistic Regression, Lauer & Bloch (2007), Sun Wei (2019) SVM.
- Inspired by Fang & Chen (2011) on **simpler mechanism**: to incorporate **prior knowledge on feature representation** layer, but **we relax to test on some possible models** rather than only one model as theirs' (SVM).

$$g: x \to T_\theta x \text{ so that } f(x) = f(g(x))$$

"Add a token to promote if any word exists in dictionary"

- Berpikir bahwa investasi sector manufaktur merupakan peluang **menarik** + **positiveInvestment**

  (Think that investment in manufacture is an interesting chance)

- Investor **khawatir** akibat krisis ini + **negativeInvestment**

  (the investors are wory for this crisis)

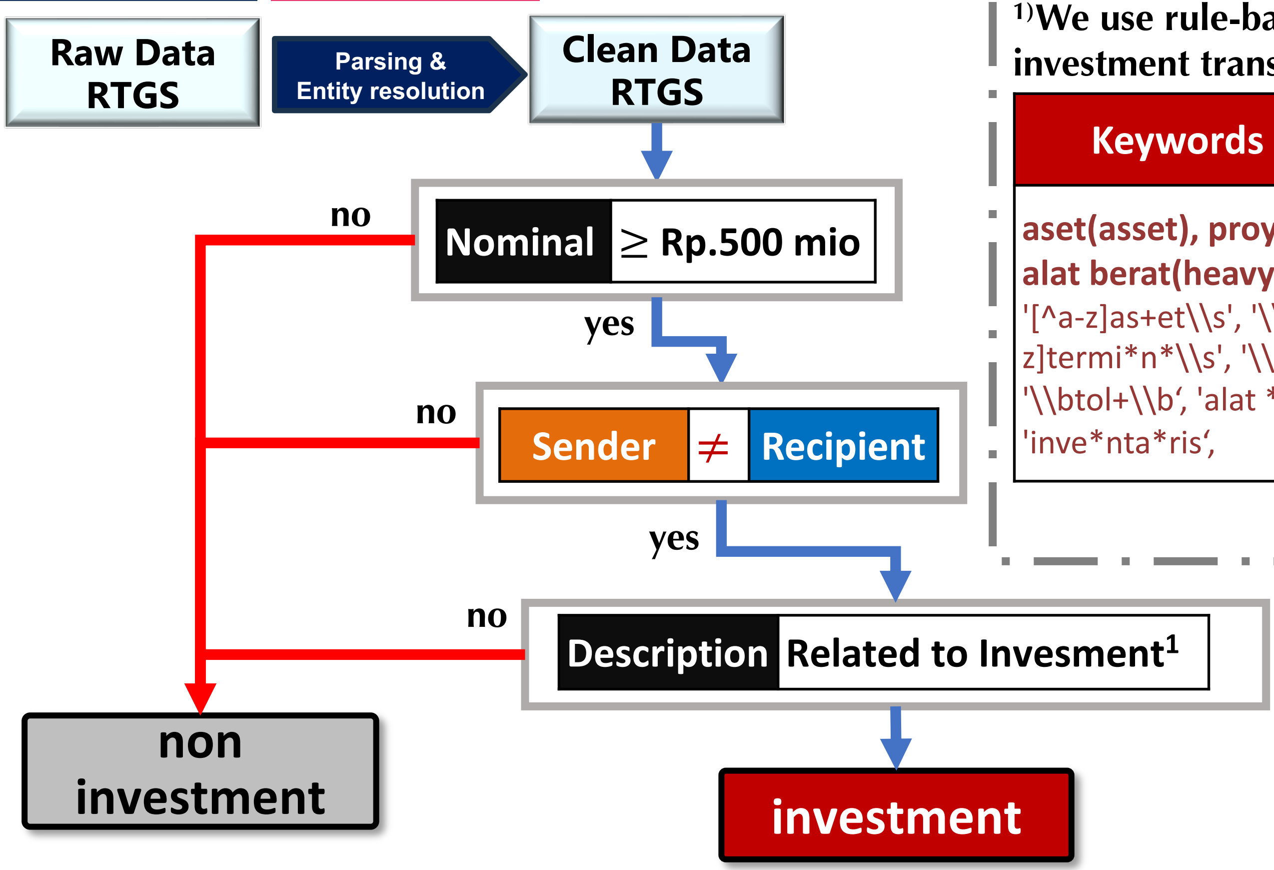
Experimental Result

Model (f)	without Prior Knowledge		with Prior Knowledge	
	F1	Error	F1	Error
SVM	80,62	24,24	**83,60**	**20,67**
Logistic Regression	79,59	24,07	82,53	20,74
Decision Tree	74,30	30,03	77,71	25,91
XGBoost	81,10	23,37	82,69	21,20

**note: with SMOTE (Chawla et al 2002)*

METHODOLOGY STRUCTURED DATA

Classification of RTGS Investment Transactions



[1]We use rule-based (keyword) approach for classifying investment transaction

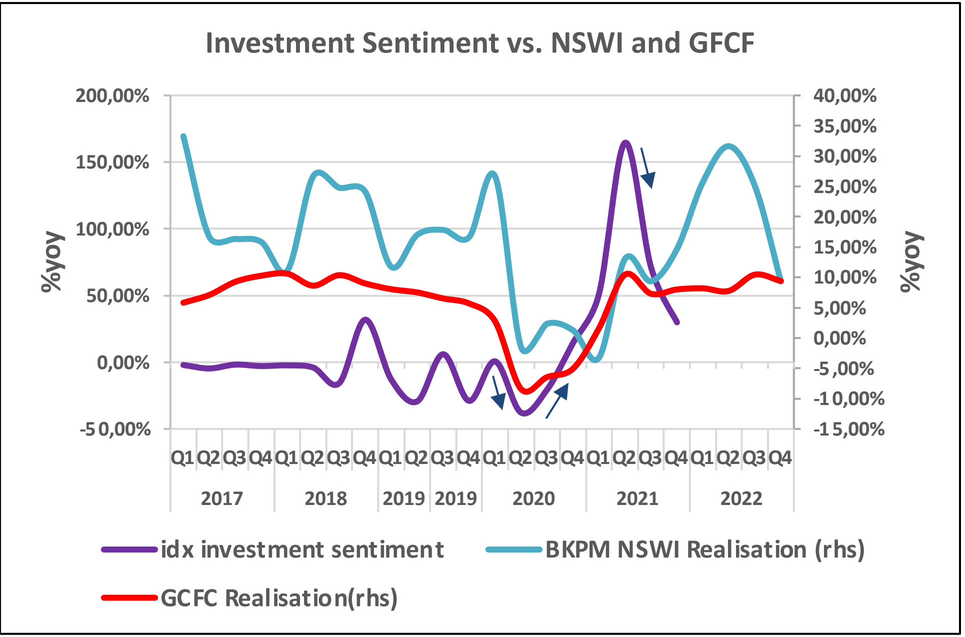
Keywords that are related to investment
aset(asset), proyek (project), tol(toll), termin(term), alat berat(heavy equipment), investaris(inventory): '[^a-z]as+et\\s', '\\bas+et\\b', '\\sas+et[^a-z]', 'proyek', '[^a-z]termi*n*\\s', '\\btermi*n*\\b', '\\stermi*n*[^a-z]', '\\btol+\\b', 'alat *be*ra*t','pe*ra*la*ta*n *(tek|tech|ind)', 'inve*nta*ris',

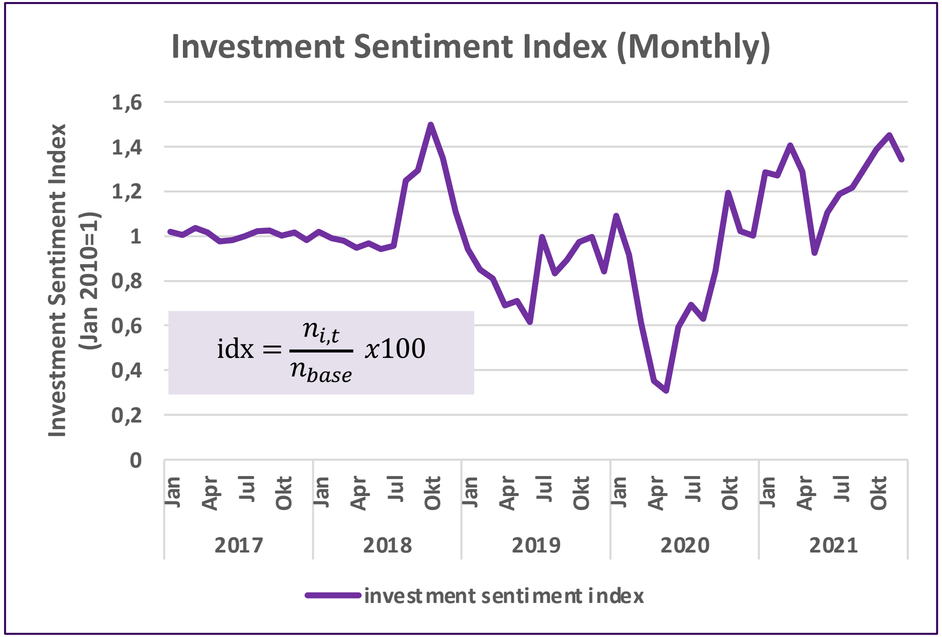
Keywords that are not related to investment
transfer dana, pindah dana, pindah buku (fund transfer/overbook): 'tra*n*s*fe*r*\\s*dana', 'pi*nda*h\\s*dana', '\\bpb\\b', 'pi*nda*h\\s*buku', '\\bpinbuk\\b'

RESULT AND ANALYSIS

Investment Sentiment Index from News for *leading indicator*

The validation results show that by the lag of 4 quarters, there are positive correlations between investment sentiment index vs. NSWI ($\rho\_Pearson$=0,77) and GFCF ($\rho\_Pearson$=0,33).

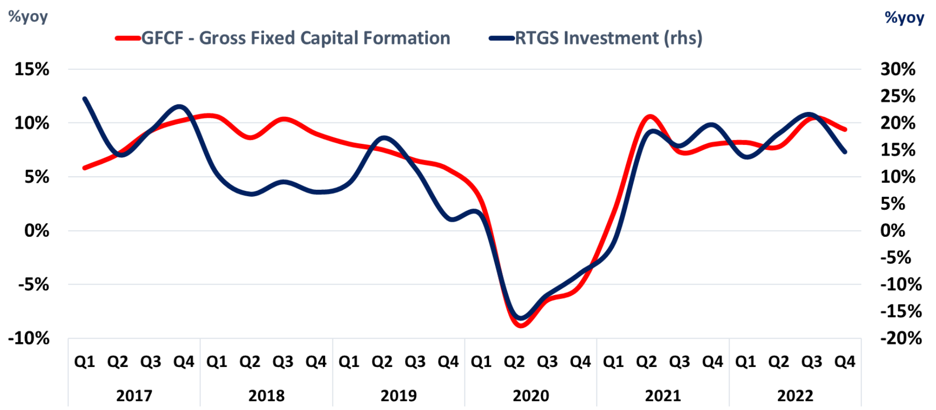




RESULT AND ANALYSIS

RTGS Investment Transactions for prompt indicator

The validation results show a high correlation between the two indicators since quarter 1-2017, including during the Covid-19 pandemic and subsequent period.



Indicators	Correlation of RTGS Investment Growth Rate with GFCF	
	Q1-2017 s.d. Q4-2022	Q1-2020 s.d. Q4-2022
Total of Gross Fixed Capital Formation	85,4%	97,6%
GCFC – Construction	83,6%	95,0%
GCFC – non Construction	78,6%	93,8%

CONCLUSION AND FUTURE WORKS

Conclusion

1. We have **proposed and alternative approached** in utilizing unstructured and structured data to construct indicators that helped to track investment direction in Indonesia.
2. Our leading investment indicator, **using text mining methodology from news through machine learning method,** can help to see the investment direction trends in Indonesia (up to 1 year). **Based on the evaluation metrices score on the model, the average F1-score of the model is 83,6 % with error rate is 20,7%**
3. Our prompt investment indicator can be **generated more quickly from payment system data using the proposed text mining methodology** compared to the GFCF indicators in GDP publications. The validation results demonstrate a high correlation between our investment indicator from the payment system and the GFCF indicators, indicating that the payment system indicator can be served as a reliable proxy for prompt investment indicators.

Future Works

1. **Developing method for sectoral investment indicators**, especially to track main sectors in Indonesia.
2. **Model accuracy improvement** e.g. further model tune up
3. **Constructing a nowcasting model for investment indicator,** involves incorporating indicators of news, payment system data, and other macroeconomic variables through the use of machine learning algorithms or econometric techniques.

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THANK YOU.