FinalReport

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1 Sentiment Analysis on Machine Translated Icelandic corpus

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2.1 Abstract

Translating English text into low-resource languages and assessing sentiment is a subject that has received extensive research attention for numerous languages, yet Icelandic remains relatively unexplored in this context. We leverage a range of baseline classifiers and deep learning models to investigate whether sentiment can be effectively conveyed across languages, even when employing machine translation services such as Google Translate and Miðeind machine translation.

2.2 Introduction

In this research endeavor, we utilized an IMDB dataset comprising 50,000 reviews, each categorized as either positive or negative in sentiment, with 25.000 being positive and 25.000 being negative. Our methodology involved the translation of these reviews using both Google Translate and Miðeind

Translate. Subsequently, we subjected all three datasets, including the original English version and the two translations, to analysis using three baseline classifiers. The primary objective was to investigate whether machine translation exerted any influence on the results of sentiment analysis and to determine the superior performer between Miðeind and Google translations. Our aim was to assess the transferability of sentiment across machine translation processes.

2.3 Machine Translations

We employed the Google Translator API, which relies on Google's Neural Machine Translation featuring an LSTM architecture. Additionally, we utilized the Miðeind Vélþýðing API for the purpose of machine-translating the reviews. The Miðeind Vélþýðing API is constructed using the multilingual BART model, which was trained using the Fairseq sequence modeling toolkit within the PyTorch framework.

2.3.1 Google Translate

All the reviews were effectively translated using the API, and the only preprocessing step performed on the raw data was the removal of
. The absence of errors during the translation process could be attributed to the API's maturity and extensive user adoption. Nevertheless, it's worth noting that the quality of Icelandic language reviews occasionally exhibited idiosyncrasies.

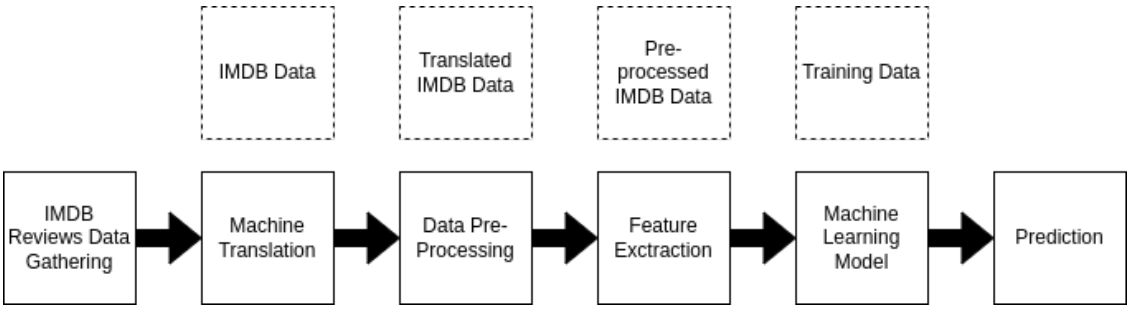
2.3.2 Miðeind

The Miðeind Translator encountered challenges when translating the English corpus into Icelandic. To prepare the text for translation, several preprocessing steps were necessary. These steps included consolidating consecutive punctuation marks, eliminating all HTML tags, ensuring there was a whitespace character following punctuation marks, and removing asterisks. Subsequently, we divided the reviews into segments of 128 tokens, which were then processed in batches by the Miðeind translator.

2.4 Pre-Processing and feature extraction

The original English dataset we lowercased, tokenized and lemmatized and removed stop words, the same was applied on the Icelandic machine translated corpus as well, in addition we also added a prefix _NEG to the words in Icelandic if the term was deemed negative to assist the vectorizer in locating negative remarks.

Three baseline classifier pipelines were created that serve as a baseline metric for our scoring for English and machine translated Google and Miðeind datasets, all classifiers use TF-IDF vectorizer, which measure the frequency of a term in each document. It measure how important the term is across all documents. We see scoring of these terms in (#logistic)



3 Baseline Classifier Evaluation

We utilized the classifiers available in the Scikit-learn Python package for implementing our machine learning models. These models were trained with their default parameters, and hyperparameter tuning was not conducted. It is important to note that superior results can be attained by fine-tuning the hyperparameters.

When assessing the statistical measures to gauge the model's performance, we applied equations 1, 2, 3, and 4.

$$Accuracy = \frac{TP + FN}{TP + FP + TN + FN} \tag{1}$$

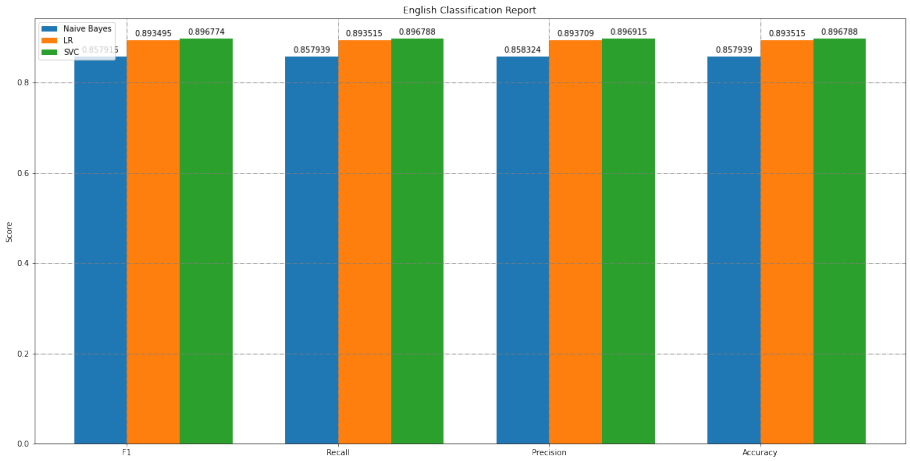
$$Recall = \frac{TP}{TP + FN} \tag{2}$$

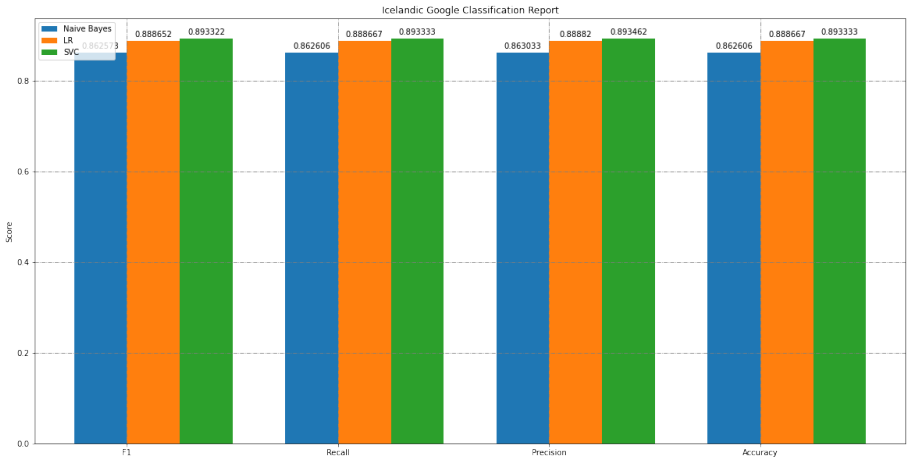
$$Precision = \frac{TP}{TP + FP} \tag{3}$$

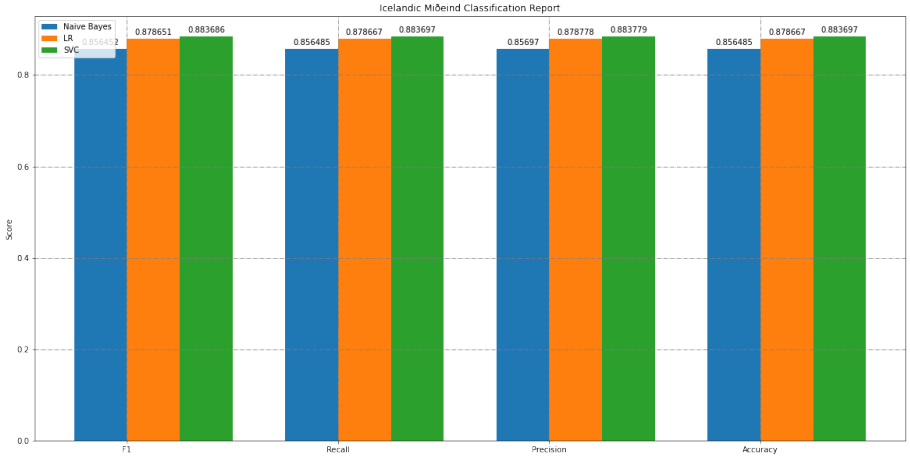
$$F1Score = \frac{2(Recall * Precision)}{Recall + Precision} \tag{4}$$

True Positive (TP) refers to correctly identified positive sentiments, while False Positive (FP) signifies incorrectly identified positive sentiments. True Negative (TN) denotes correctly identified negative sentiments, and False Negative (FN) represents incorrectly identified negative sentiments.

The data was divided into training and test sets, with 67% (33,500 reviews) allocated for training the models and 33% (16,500 reviews) reserved for testing the model's performance.







In this visual representation of the classification report encompassing all classifiers, we observe that Support Vector Classification (SVC) outperformed other models when applied to the data. All models were trained with 33,500 reviews and tested with 16,500. If we establish SVC as our baseline comparative model and employing a weighted F1 score as our evaluation metric, we can discern the following results across different datasets: In the English dataset, the F1 score reached 89.67%, the translated Miðeind dataset achieved an F1 score of 88.36%, and the Google dataset attained an F1 score of 89.33%. These figures suggest that sentiment analysis can carry across Machine Translation when utilizing state-of-the-art machine translation APIs. The loss in accuracy during translation is minimal, with only a 1.31% and 0.34% drop in accuracy, favoring Google's performance.

3.1 Support Vector Classifier

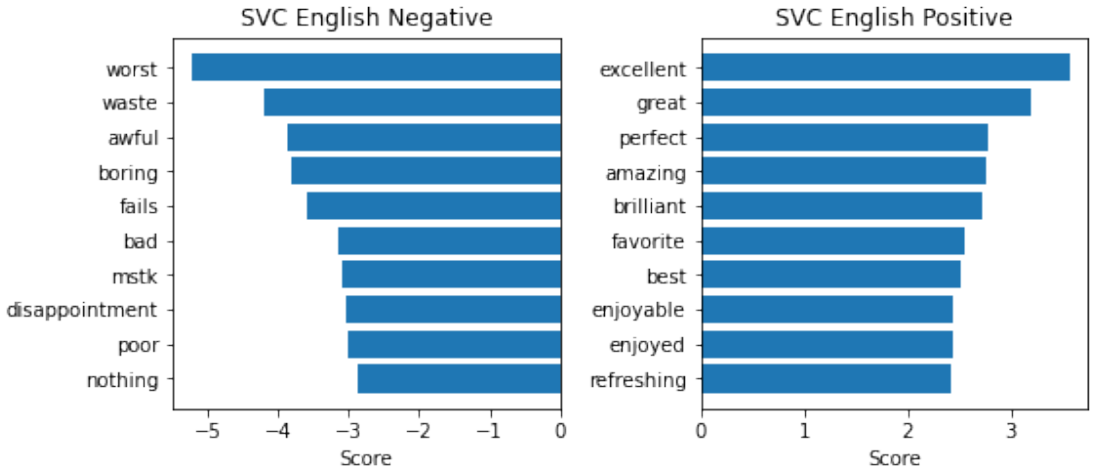
The SVC (Support Vector Classifier) was the best machine learning algorithm in classifying sentiment, it is a linear binary classification algorithm, were the result is defined as zero or one in binary models.

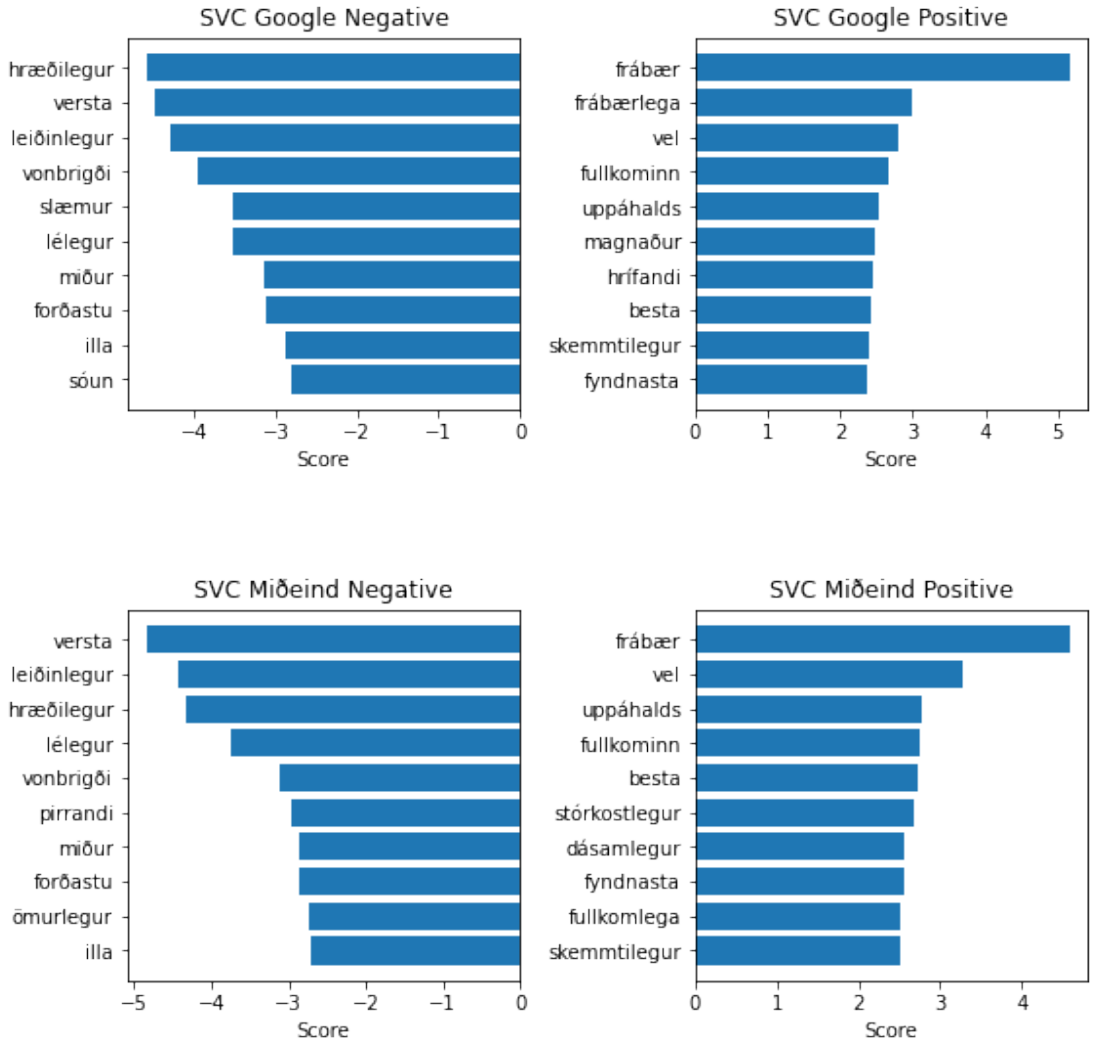
English Sentiment	Precision	Recall	F1-Score
negative	0.90	0.89	0.90
positive	0.89	0.91	0.90

Google Sentiment	Precision	Recall	F1-Score
negative	0.90	0.88	0.89
positive	0.89	0.90	0.89

Miðeind Sentiment	Precision	Recall	F1-Score
negative	0.89	0.88	0.88
positive	0.88	0.89	0.89

When we trained the class it gives us a list of coefficients that represent the relationship between the input variables and the output variable in the model. The coefficient can be interpreted as the relative importance of the word it's classified to, in this case negative or positive. In this chart we can see the top 10 negative and positive values, for a sentence to be positive in this case, it has to have a value of one.





3.2 Logistic Regression

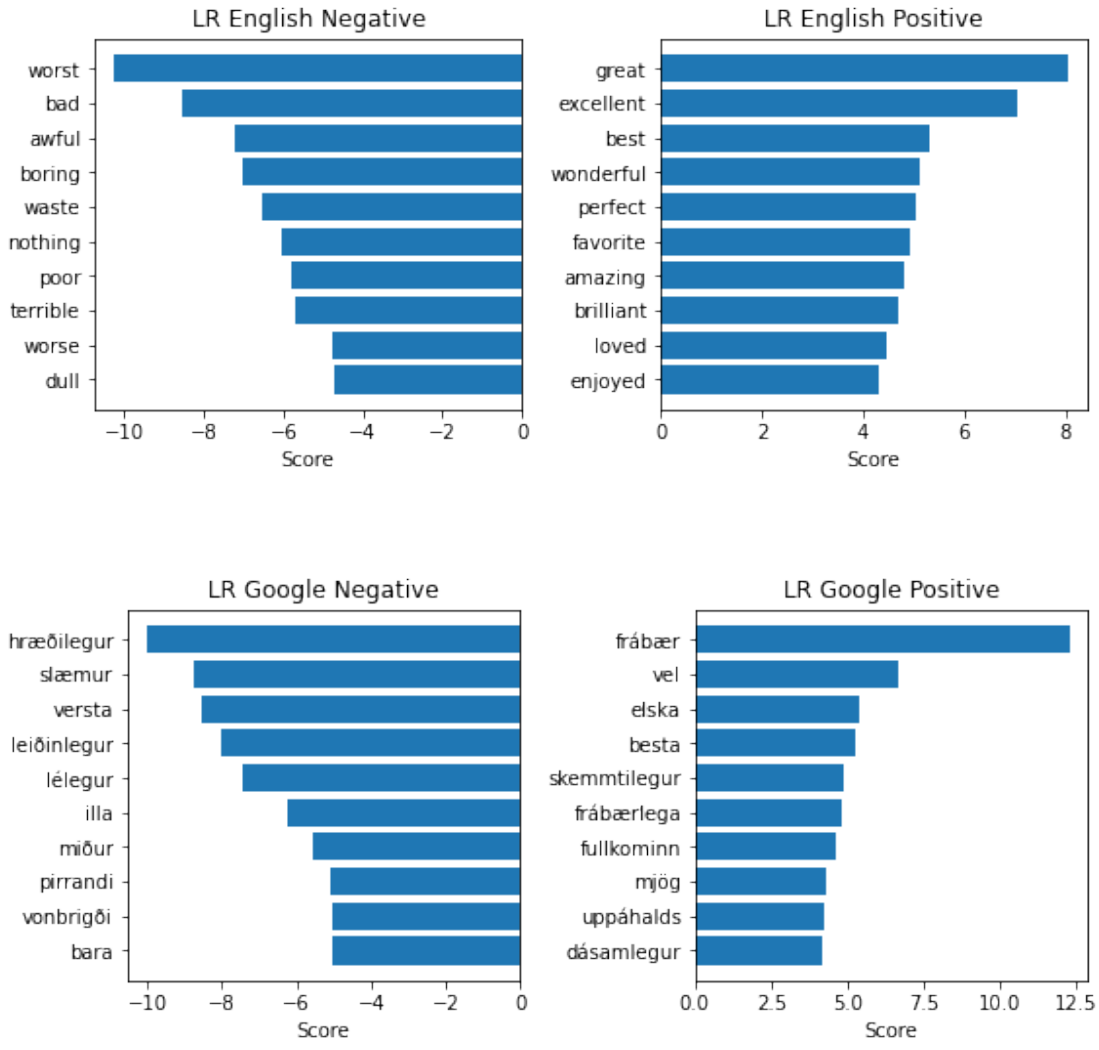
Logistic Regression is a binary classification algorithm, were the result is defined as zero or one in binary models.

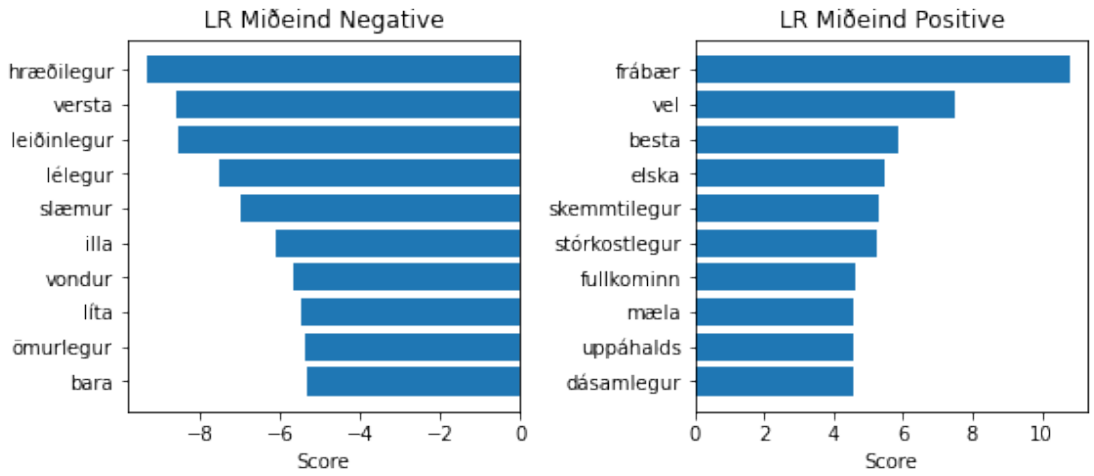
English Sentiment	Precision	Recall	F1-Score
negative	0.90	0.88	0.89
positive	0.89	0.91	0.90

Google Sentiment	Precision	Recall	F1-Score
negative	0.90	0.88	0.89
positive	0.88	0.90	0.89

Miðeind Sentiment	Precision	Recall	F1-Score
negative	0.88	0.87	0.88
positive	0.87	0.89	0.88

When we trained the class it gives us a list of coefficients that represent the relationship between the input variables and the output variable in the model. The coefficient can be interpreted as the relative importance of the word it's classified to, in this case negative or positive. In this chart we can see the top 10 negative and positive values, for a sentence to be positive in this case, it has to have a value of one.





3.3 Naive Bayes

Naive Bayes is a classifier for multinomial models, although we employed it for binary classification

English Sentiment	Precision	Recall	F1-Score
negative	0.85	0.87	0.86
positive	0.87	0.84	0.86

Google Sentiment	Precision	Recall	F1-Score
negative	0.85	0.88	0.86
positive	0.88	0.85	0.86

Miðeind Sentiment	Precision	Recall	F1-Score
negative	0.84	0.87	0.86
positive	0.87	0.84	0.85

3.4 Testing

4 Next Steps

Next steps are using classifiers that have scalabe sentiment and start looking into deep learning models such as BERT.

5 Burndown Chart

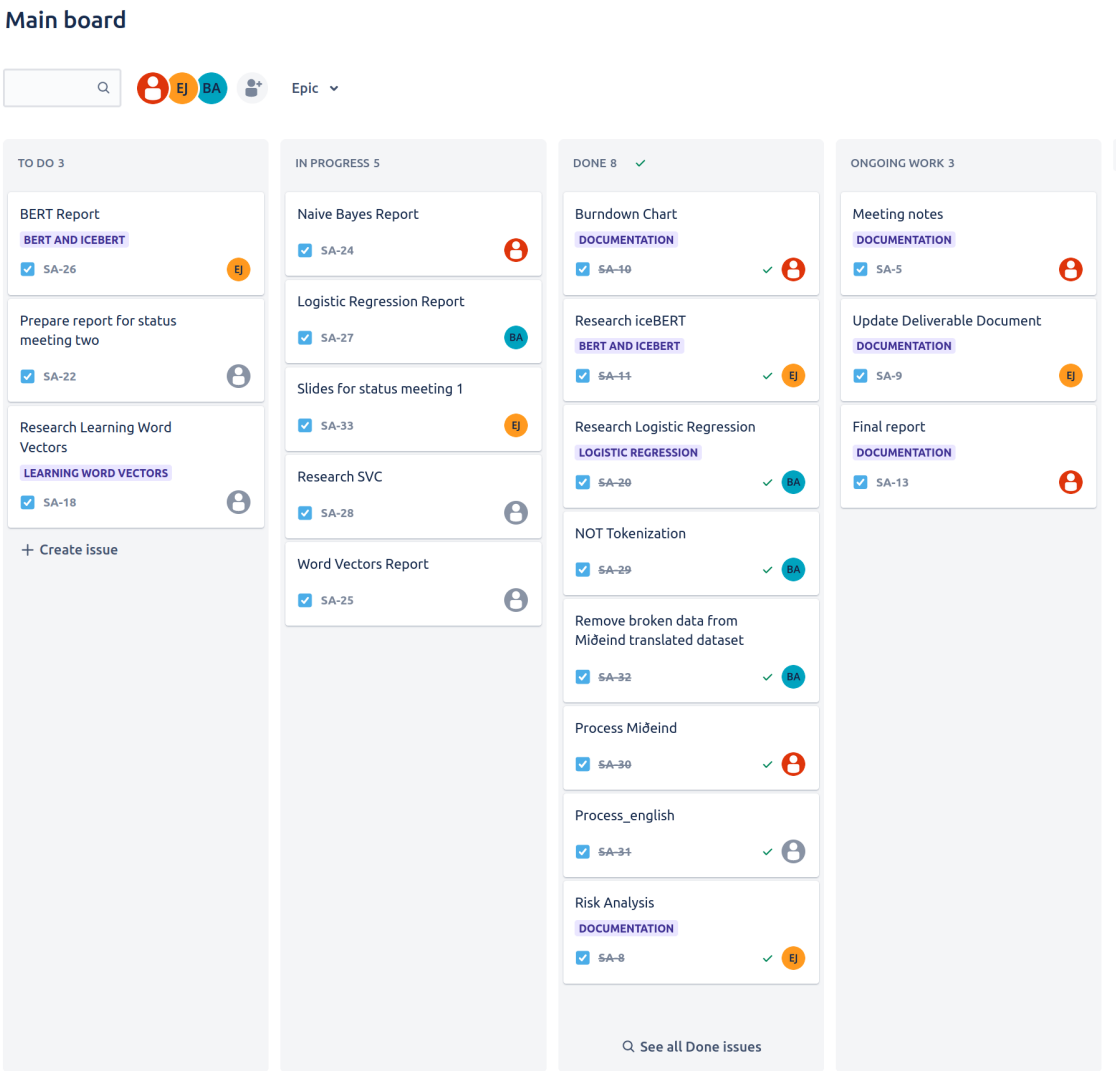
Given the research-oriented nature of our project, as opposed to corporate work, we opted for a Kanban approach rather than Scrum. We started well in advance, with initial preparations and research activities commencing in late July to early August. This timeframe allowed us to

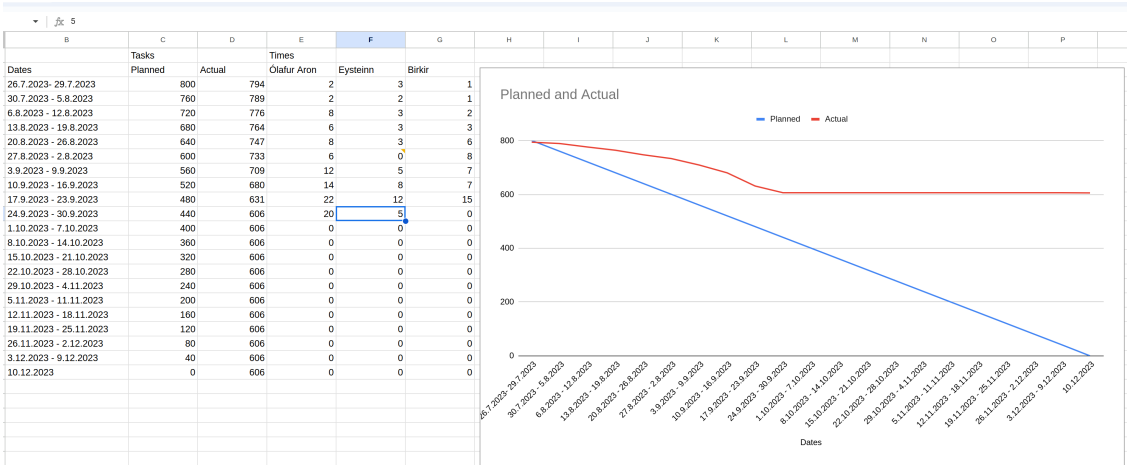
familiarize ourselves with the intricacies of machine learning, particularly since only one team member possessed prior experience in Machine Learning and Deep Learning.

We've allocated a collective 40 hours per week for all team members, distributed across a span of 20 weeks, aiming to complete this project within this timeframe. This amounts to a total of 800 hours dedicated to the project. We expect the burndown to go under the planned line in October since we are picking up the pace but still keeping the 40 hours as a median.

The sum of the spent hours for each team member is - Ólafur Aron Jóhannsson (100) - Eysteinn Örn (44) - Birkir (50)

The reason Ólafur Aron has accumulated more hours is due to the fact that he will be departing abroad in late November and returning in early December, during which period his hours will be reduced.





		Tasks		Times		
Dates	Planned	Actual	Ólafur Aron	Eysteinn	Birkir	
26.7.2023- 29.7.2023	800	794	2	3	1	
30.7.2023 - 5.8.2023	760	789	2	2	1	
6.8.2023 - 12.8.2023	720	776	8	3	2	
13.8.2023 - 19.8.2023	680	764	6	3	3	
20.8.2023 - 26.8.2023	640	747	8	3	6	
27.8.2023 - 2.8.2023	600	733	6	0	8	
3.9.2023 - 9.9.2023	560	709	12	5	7	
10.9.2023 - 16.9.2023	520	680	14	8	7	
17.9.2023 - 23.9.2023	480	631	22	12	15	
24.9.2023 - 30.9.2023	440	606	20	5	0	
1.10.2023 - 7.10.2023	400	606	0	0	0	
8.10.2023 - 14.10.2023	360	606	0	0	0	
15.10.2023 - 21.10.2023	320	606	0	0	0	
22.10.2023 - 28.10.2023	280	606	0	0	0	
29.10.2023 - 4.11.2023	240	606	0	0	0	
5.11.2023 - 11.11.2023	200	606	0	0	0	
12.11.2023 - 18.11.2023	160	606	0	0	0	
19.11.2023 - 25.11.2023	120	606	0	0	0	
26.11.2023 - 2.12.2023	80	606	0	0	0	
3.12.2023 - 9.12.2023	40	606	0	0	0	
10.12.2023	0	606	0	0	0	

6 Risk Analysis

Risk	Likelihood (1-5)	Impact (1-5)	Responsibility	Mitigation Strategy
Resource Constraints (Time and Computing Power)	4	5	Eysteinn	Prioritize key features and models that are critical to the project. Consider using cloud computing resources.
Training stops/Computer crashes	4	4	Ólafur	Regular backups and distributed training could mitigate this risk.
Sprint/Project delay	3	5	Ólafur	Address the problem in the standup's and frequent reassessments.

Risk	Likelihood (1-5)	Impact (1-5)	Responsibility	Mitigation Strategy
Incompatibility of Translation APIs	3	3	Birkir	Have fallback methods for each API, and make the system modular to easily swap out one service for another.
Classifier Model Inefficiency	3	3	Eysteinn	Use baseline models for initial testing before using more complex models like BERT, roBERTa, and IceBERT.
Overfitting in Model Training	2	4	Birkir	Utilize techniques such as cross-validation and dropout layers.
Illness in team	2	4	Whole Team	Cross-training and comprehensive documentation can help other team members pick up the slack. Tries not getting other team members sick.
API Rate Limiting or Costs	2	3	Birkir	Caching translated data and batch processing could help in minimizing the number of API calls.

Risk	Likelihood (1-5)	Impact (1-5)	Responsibility	Mitigation Strategy
A team member quits	1	5	Whole Team	Having a documented and modular project architecture allows for easier transition of responsibilities.
External Dependency Failures (APIs down)	1	2	Whole Team	Have a contingency plan, such as a local translation model otherwise wait and focus on a different task

7 Meeting Notes

In addition to all data gathered we also tried to keep meeting notes as far back as 26. July.

Fundur 26.7.2023

Nemendur stofna hóp og ræða sín á milli hugmyndir að lokaverkefni, Discord rás er stofnuð

Fundur 6.8.2023

Nemendur hittast og ræða sín á milli hugmyndir sem þeir vilja sjá í Lokaverkefni, Eysteinn hefur verið að vinna í verkefni tengt gervigreind og máltækni og voru allir nemendur sammála að við viljum vinna í verkefni tengt því, hugmyndir sem komu upp á fundi voru meðal annars(á Ensku:)

- Poetry (Help students in literature classes)
    - Analyze poetry (merkja stuðla og höfuðstafi)
    - Generate poetry in Icelandic
- Help with Icelandic vocabulary and sentences. AI can invent new sentences or questions in areas where students are struggling and can receive feedback from the system
- GameQA extensions
    - Focus on more complicated questions
- Multiplayer language learning game
    - Game where users compete against each in Icelandic learning challenges
    - Can be gamified where you level up
    - Could even be tied to the Poetry and Icelandic vocabulary ideas (mark Stuðlar and Höfuðstafir/What is wrong/right with this sentence, etc)
- Sentiment analysis for Icelandic text (who is positive/who is negative, could be interesting to see what news stations is the most positive/negative)
- Icelandic text simplification tool
    - Could be a benefit to foreign, young and even native-Icelandic speakers to be able to have a text (usually written by a Lawyer) and parse it to something that is human readable (from lawyer-speak)

Farið var yfir landslagið í gervigreind og máltækni og hugmyndir ræddar.
Ákveðið var að hittast aftur eftir þrjá daga og undirbúa tölvupóst til að senda á Hrafn Loftsson.

Fundur 3.8.2023

Nemendur ræða lítilllega á Discord og skipuleggja fund og ræða um lokaverkefnið

Fundur 4.8.2023

Fundur skipulagður

Fundur 6.8.2023

Miðeind, huggingface or fleiri auðlindir tengdar gervigreind eru skoðaðar, iceBERT og BERT módelið

Fundur 9.8.2023

Hittust nemendur og var Eysteinn með póst tilbúinn sem nemendur lásu yfir.. Var einnig rætt um Miðeind API og fleiri gervigreindar máltæknis hugmyndir sem koma til greinia, sendur var tölvupóstur á Hrafn með tillögum að verkefni, verkefnin sem voru valin voru eftirfarandi

- Text simplification, einföldun á flóknum íslenskum texta.
    - Einfalda og auðvelda tungumálið fyrir bæði útlendinga og Íslendinga (einfalda lagabálka og/eða lög).
- Gervigreind til að laga málfar og stafsetningu.
    - Hins vegar er miðeind með svipað tól nú þegar sem kallast yfirlestur
- GameQA extension - með einbeitingu á flóknum spurningum og svörum.

kannski er hægt að laga það svona.

- Sentiment analysis - Skoða hvort texti sé jákvæður eða neikvæður.
    - Gætum þá kannað hvaða frétta miðill er jákvæðastur/neikvæðastur.
- Ljóða sköpunar gervigreind - Skapa og greina ljóð , finna stuðla, höfuðstafi og semja ljóð eftir prompt.
    - getur hjálpað nemum í grunnskóla og framhaldskóla að skilja íslensk ljóð.
- Sjálfvirkur lestur, flokkun og áframsending á íslenskum tölvupósti.
    - það er að ef póstur er sent á hjalp@fyrirtæki.is og inniheldur setningu með orðinu "bókhaldskerfið" þá er það áframsent á bokhaldskerfi@fyrirtæki.is sjálfkrafa.

Fundur 11.8.2023

Hrafn svarar pósti og leggur til að við munum taka að okkur viðhorfsgreiningu sem lokaverkefni, ræddu nemendur sín á milli að við værum sammála að þetta væri góður kandídat að verkefni.

Fundur 14.8.2023

Ákveðið var að svara Hrafni og velja dagsetningu til að funda með honum

Fundur 16.8.2023

Hrafn svarar og fundur næsta dag kl 10 var bókaður

Fundur 17.8.2023 með Hrafn Loftssyni

Hrafn lýst best á sentiment analysis, munum við halda áfram með að gera lokaverkefnis-tillögu með það í huga

- Skoða aðra sem hafa þýtt frá ensku á annað tungumál
- Þýða imdb yfir á íslensku með vélþýðing frá miðeind og google translate
- Skali og/eða boolean á viðhorfsgreiningu
- Handvirkt þýða texta á 1000 review og skoða muninn hvort líkanið gefur aðra niðurstöðu fyrir
- handvirka breytingu (væri þá áhugavert að hafa skal í þessu tilviki)
- Logistic regression til að skoða sentiment analysis á móti tauganeti
- Íslenskur gagnagrunnur fyrir viðhorfsgreiningu
- Prófa mismunandi vélþýðandalíkön/gervigreindarlíkon
- Framlagið eru tilraunirnar sjálfar
- Hvaða aðferð notuðu þeir
- Post-editing?
- Nota yfirferð frá Miðeind?
- Hversu mikið af gögnum þarf að þjálfa netið til að niðurstaðan sé góð? 5000/10000/25000?
- Google-a Vélþýðingar á þekktum gögnum

Fundur 19.8.2023

Byrjað er á Lokaverkefnis tillögu skjali fyrir verkefnið sem nemendur ákváðu er viðhorfsgreining á íslenskum texta

Fundur 21.8.2023

Farið er yfir skjalið og líka rætt mismunandi tauganet sem við ætlum að beita í verkefninu

Fundur 3.9.2023

Júlíus og Ólafur Aron fóru yfir JIRA borð og ræddu um áhættugreiningu og skjölun á því, talað var um að halda um status á verkefninu á JIRA, ákveðið var að halda annan fund samdægurs því vantaði Birki og Eystein

Fundur 3.9.2023

Allir nemendur fara yfir JIRA borð og búa til tösk sem þeir assigna á sig, við klárum að gera vélþýðingar og bætum við töskum sem við á, mælum okkur mót við Sigurjón um að spjalla á þriðjudag.

Fundur 4.9.2023

Svar frá Sigurjóni að taka spjall næstkomandi dag

Fundur 5.9.2023

Fundur með Sigurjóni, farið yfir stöðuna og sýnt JIRA borðið, rætt um scrum og kanban, verkefnatillaga kynnt og útdrög að önn sett upp.

Fundur 8.9.2023

Rætt saman og skoðað hvar allir eru staddir, Naive Bayes, Word Vectors, BERT og Logistic Regression

Fundur 9.9.2023

Sigurjón ekki lengur umsjónarmaður í verkefni heldur Hrafn

Fundur 11.9.2023

Stefán Ólafsson er líka leiðbeinandi í verkefninu, ákveðið að halda fund kl 9 næsta dag

Fundur 12.9.2023

Fundur haldinn kl 9, nemendur ræddu við Stefán og Hrafn um stöðu verkefnis og var ákveðið að halda fundi kl 9 á þriðjudögum, rætt var um að meta muninn á vélþýðingum google translate og miðeind og skoða baseline classifiera eins og naive bayes, logistic regreesion

Fundur 16.9.2023

Júlíus og Ólafur ræða saman og kemst Júlíus að þeirri niðurstöðu að hann er að íhuga að segja sig úr verkefninu.

Fundur 17.9.2023

Birkir og Ólafur ræða um morguninn og fara yfir logistic regression og naive bayes. Júlíus og Ólafur ræða aftur saman og er Júlíus alveg farinn úr verkefninu og eru við þá orðnir 3, Birkir,

Fundur 18.9.2023

Stefán Óla fær stöðuuppfærslu sem er svohljóðandi Sælir @stefanola , staðan er þannig að ég og Birkir erum komnir á gott ról með þá classifiera sem við töluðum um, þá Naive Bayes(Multinomial) og Logistic Regression, við höfum forunnið Google Translate gagnasettið með því að lowercasea, lemma og fjarlægja stopporð og trainað módelin og erum við að fá umbb 86-90% accuracy á baseline classifiera. Við ætlum að byrja á skýrslu sem mun fara yfir þær niðurstöður sem komnar eru, Eysteinn er búinn að vera vinna í iceBERT og talaði hann um í gær að mögulega þyrfti hann að þjálfa það frá grunni. Næst á dagskrá er að forvinna miðeindarsettið og líka keyra módelin á ensku gagnasettin til að bera saman, eftir það færum við að skoða SVC/word2vec. Það má líka nefna að ég og Júlíus ræddum saman um helgina og af persónulegum ástæðum hefur hann ákveðið að segja sig úr verkefninu og við erum þá þrír. Við höldum áfram með það sem lagt var með í byrjun en munum þá aðlaga tillöguskýrsluna til að endurspegla stöðuna.

Fundur 19.9.2023

Rætt við Hrafn og farið yfir stöðuna, hann bendir á að muna tímaskráningu og byrja á skýrslu.

Fundur 20.9.2023

Fundur kl 20, nemendur hittast og fara yfir hvað komið er, Naive Bayes, Logistic Regression og iceBERT, skoða að þurfa að endurtranslate-a miðeind því gögnin eru skrítin og eru að birta stjörnur.

Fundur 21.9.2023

Eysteinn og Ólafur Aron ræða aðeins stöðuna, fara yfir transformera og lokaskýrslus

Fundur 22.9.2023

Birkir og Ólafur Aron ræða um þýðingar og datasettið

Fundur 24.9.2023

Nemendur ræða um BERT model og hvað progress er, þurfum að ræða við kennara til að leysa nokkra hluti

Fundur 25.9.2023

Nemendur fara aftur yfir stöðuna fyrir stöðufund næsta dag

Fundur 26.9.2023

Fundur með Hrafn og rætt um stöðufund 3 Október