AI FOR HEALTHCARE

Analysis on Depressive Social Media Texts

SCSE20-0985

Student: Neo Shun Xian Nicholas

Supervisor: Associate Professor Erik Cambria

CONTENTS

- 00. Introduction & Objective
- 01. Challenges of Detecting Depression
- 02. Explorations
 - Tasks
 - Datasets
 - Models, APIs & Framework

03. Tasks

- Emotion Classification
- Emotion Intensity Prediction
- Text Summarisation (Subtask)
- Emotion-cause Pair Extraction

04. Future Work

OO INTRODUCTION & OBJECTIVE

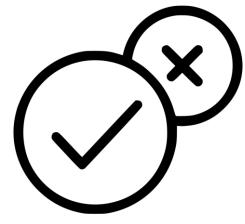
INTRODUCTION



Depressed Silhouette Man [1]

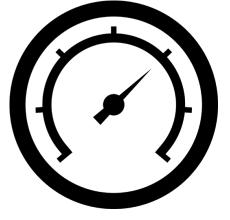
OBJECTIVE

To leverage on the use of Deep Learning and Natural Language Processing (NLP) to do an in-depth analysis on depressive social media contents



Yes/No Logo [3]

Predicting whether a particular piece of text contents sentiment of depression



Metre [4]

Creating a depression metric and predict depression scores for all data labelled as depressive content



















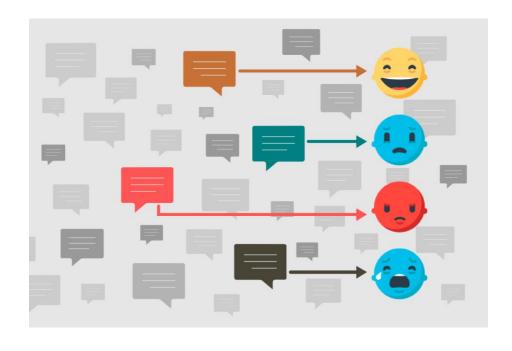
Emotions [5]

the model can extract depressive emotion and the cause of depression from text clauses

01 CHALLENGES OF DETECTING DEPRESSION

SENTIMENT ANALYSIS VS EMOTION ANALYSIS

- Both differs in terms of how unstructured text data are being analysed
- Sentiment analysis merely separates the data points and determine whether the text conveys a negative, neutral or positive feeling
- On the other hand, emotion analysis consists of deeper analysis that dives down into the psychology of one's emotion and behaviour



Sentiment Analysis [6]

WHY IS DETECTING DEPRESSION FROM TEXT HARD?

- The labels of the text "depress/not depressed" cannot be directly equated with the labels "positive/negative".
- Signs of depression are subtle and not obvious
- These subtle indications may be reflected in the nuances of someone's language
- More in-depth psychological analysis should be conducted to assess the text data



Expressions [7]

02 EXPLORATIONS

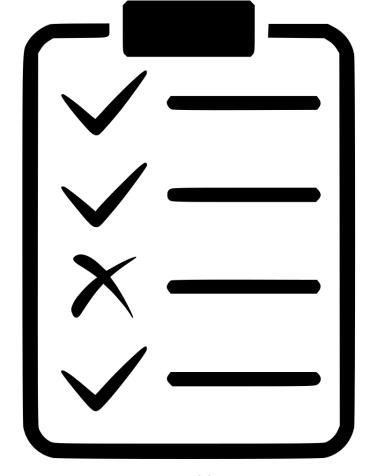
TASKS

Emotion Classification

Emotion Intensity Prediction

Text Summarisation (Subtask)

Emotion-cause Pair Extraction



MAIN DATASETS

Toy Dataset

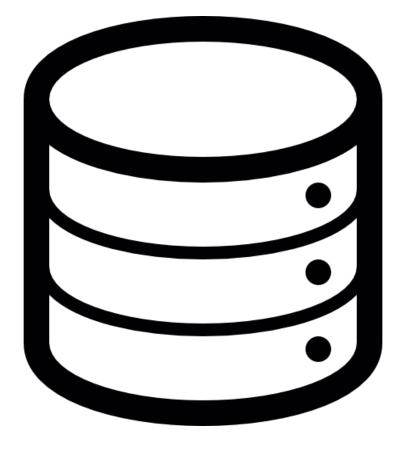
- 8000 : 2314 (non-depressive entries : depressive entries)
- Used in Emotion Classification task

Twitter Dataset (Short Text)

- 2357 : 844 (non-depressive entries : depressive entries)
- Used in all tasks

Reddit Dataset (Long Text)

- 1292 : 1437 (non-depressive entries : depressive entries)
- Used in all tasks



Database [9]

WASSA 2017 EMOINT DATASET

- Obtained from the official competition website.
- In this project's context the datasets will be used solely as the training data for the Emotion Intensity Prediction task
- Emotions in these datasets
 - Anger
 - Fear
 - Sadness

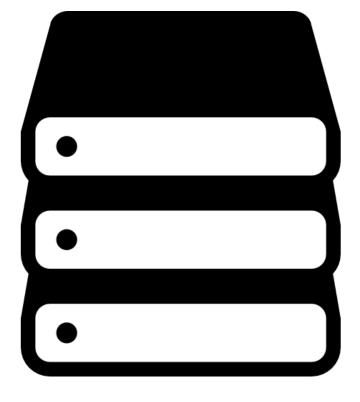
	Text	Label	Score
0	@ZubairSabirPTI pls dont insult the word 'Molna'	anger	0.479
1	@ArcticFantasy I would have almost took offens	anger	0.458
2	@IllinoisLoyalty that Rutgers game was an abom	anger	0.562
3	@CozanGaming that's what lisa asked before she	anger	0.500
4	Sometimes I get mad over something so minuscul	anger	0.708

	Text	Label	Score
0	I know this is going to be one of those nights	fear	0.771
1	This is #horrible: Lewis Dunk has begun networ	fear	0.479
2	@JeffersonLake speaking of ex cobblers, saw Ri	fear	0.417
3	@1johndes ball watching & Enjo'd header wa	fear	0.475
4	Really#Jumanji 2w/ The Rock, Jack Bla	fear	0.542

	Text	Label	Score
0	@1johndes ball watching & Rojo'd header wa	sadness	0.583
1	A pessimist is someone who, when opportunity k	sadness	0.188
2	A .500 season is all I'm looking for at this p	sadness	0.688
3	Stars, when you shine,\nYou know how I feel.\n	sadness	0.292
4	All I want to do is watch some netflix but I a	sadness	0.667

THE NEED FOR MULTIPLE DATASETS

- Analysis of depressive text can be more generalised
- Twitter datasets are shorter in length due to the limitations on the number of characters that could be written and posted
- Reddit datasets are much longer as there are no restrictions on the number of characters that could be written and posted



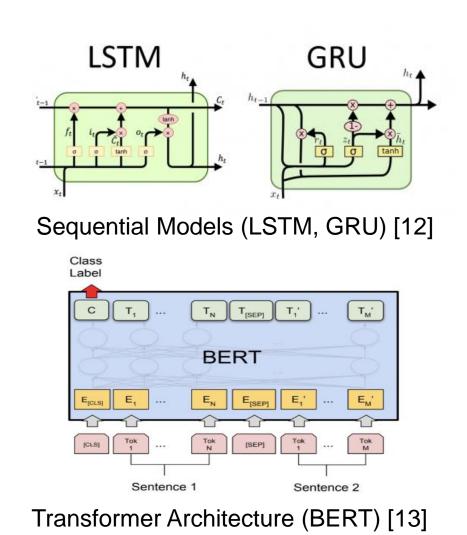
Database [10]

DATA CLEANING

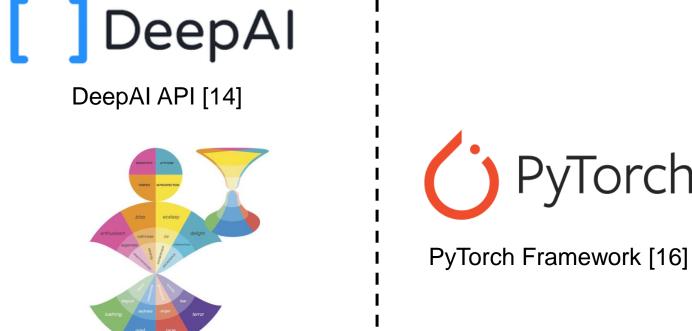
- Contraction removal
- Remove '@' and '#' from tweets
- Remove emojis
- Remove numbers
- Lowercase all letters
- Remove letters who appeared more than twice in the text.
- Remove stopwords
- Lemmatise the text



MODELS, APIS & FRAMEWORK





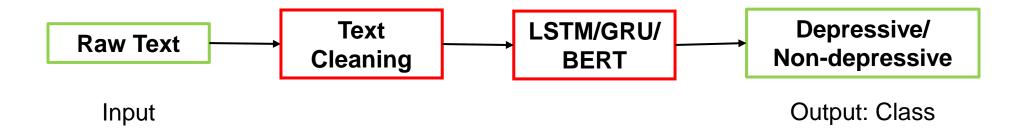


03 TASKS

03A EMOTION CLASSIFICATION

PIPELINE

Aim: Classify if a text is depressive or non-depressive



HYPERPARAMETERS

Hyperparameters Held Constant (Sequence Model)

- Number of Epochs: 15
- Learning Rate: 5e-04
- Hidden Dimension: 512
- Number of RNN layers: 4
- Dropout: 0.5
- Batch Size: 32
- Optimiser: Adam

Hyperparameters Held Constant (Transformer Model BERT)

- Number of Epochs: 2
- Learning Rate: 5e-05
- Batch Size: 16
- Optimiser: AdamW

DATA CLEANING TECHNIQUES

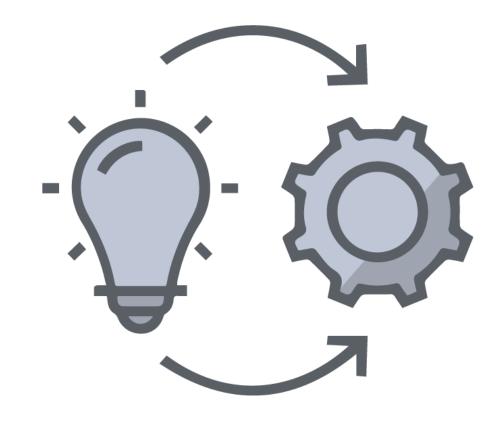
- 1. Contractions removal
- 2. Keep alphabets only
- 3. Lowercase all letters
- 4. Remove letters who appeared more than twice in the text.
- 5. Remove stopwords
- 6. Lemmatise the text



Cleaning [17]

IMPLEMENTATION

- All datasets split into their corresponding train and validation sets
- 80% train data and 20% validation data
- Custom Data Loader classes were written to load the data for the sequence models and BERT
- Model building
- Compare model performances



Idea [18]

PERFORMANCE METRICS

- Validation Accuracy
 - Measures how well the model predicts by comparing the predictions with the ground truth values in terms of percentage
- F1-score
 - Measure of a model's accuracy by combining the precision and recall of the model, and it is defined as the harmonic mean of the model's precision and recall.
 - Defined as F1 = (2 * Precision * Recall) / (Precision + Recall)
- Area under the Curve (AUC)
 - Represents the degree of separability and it tells how much the model is capable of distinguishing between classes.

MODEL PERFORMANCES

Model	Validation Accuracy	F1 Score	AUC
LSTM	0.9834	0.9834	0.99234
Bi LSTM	0.9806	0.9801	0.99436
GRU	0.98168	0.9812	0.99267
Bi GRU	0.97953	0.979	0.98916
BERT	0.9989	0.9989	1

Model	Validation Accuracy	F1 Score	AUC
LSTM	0.72768	0.7222	0.80175
Bi LSTM	0.73539	0.7362	0.80849
GRU	0.70414	0.7036	0.78461
Bi GRU	0.70698	0.7063	0.79508
BERT	0.7883	0.7874	0.8726

Toy Dataset

Model	Validation Accuracy	F1 Score	AUC
LSTM	0.8364	0.8272	0.89714
Bi LSTM	0.86642	0.8776	0.9408
GRU	0.81985	0.8072	0.90907
Bi GRU	0.85723	0.8679	0.93939
BERT	0.8832	0.897	0.95

Twitter Dataset

RE-EXAMINING THE TOY DATASET

- May have a flaw in the toy dataset due to the 'near to perfect' metric scores.
- Two methods to determine if the toy dataset is reliable and still can be used for other tasks ahead.
 - Rough Observation
 - Inter-annotator Agreement



Thinking man [19]

ROUGH OBSERVATION

Text	Label
The Oil that has the Potential to Fight Migraines, Depression, Anxiety, & Even Cancer http://www.healthy-holistic-living.com/oil-potential-cure-migraines-depression-anxiety-even-cancer.htmlÃ,ÂÀ€¦	
@ the ppl on my TL that liked the tweet about how self-care will cure depression which essential oils will stop my hallucinations & paranoid delusions?	1
I call BS if anyone deserves credit its president Obama for putting the brakes on the worse recession in our history that almost lead to a depression if not for Obama & his adms getting the economy that GWB & the reps had managed to almost demolish back on its tracks. #REALNEWS	
my depression: https://twitter.com/kanyewest/status/989142253468708864Ã, â€¦	1
Social support, rest, ritual, food, storytelling, and touch are all common among cultural practices for #postpartum #depression. F Parks #GOLDQuotes #PPD #PPMAD #maternalhealth	1

Text	
Good morning everyone	0
Busy rest of the daymeeting with prospective clients, college students who want to be "Collegepreneurs" . Later!	0
@kathrynryn not since friday but its all good its all good	0
@alecstanworth That's nothing: http://bit.ly/better-bragging-rights and she resigned too	0
slept too much, so, no school to me	0

INTER-ANNOTATOR AGREEMENT

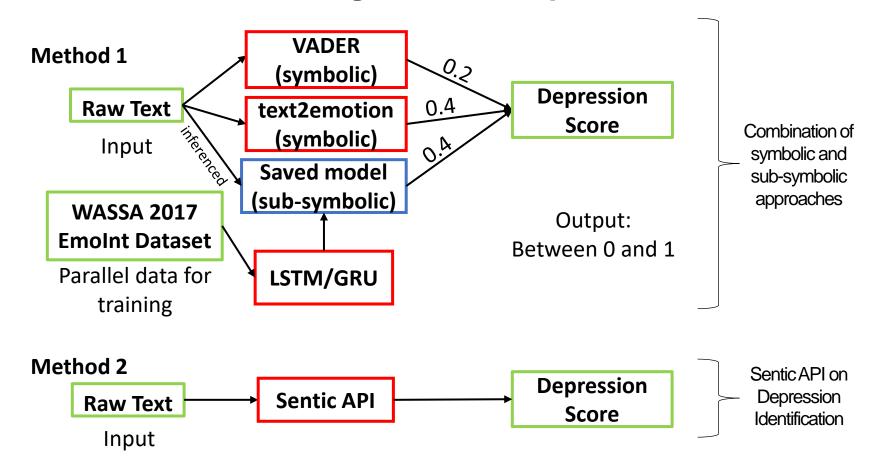
Get 2 annotators to annotate a sample of the dataset and see how much agreement they have with each other and how much agreement they have with the ground truth labels by measuring the Cohen's Kappa coefficient

Annotator A	Annotator B	Cohen's Kappa Coefficient
Annotator 1	Annotator 2	0.81073
Ground Truth	Annotator 1	0.20354
Ground Truth	Annotator 2	0.19027

03B EMOTION INTENSITY PREDICTION

PIPELINE & IMPLEMENTATION

Aim: Estimate the magnitude of depression from text



DATA CLEANING TECHNIQUES

- 1. Contractions removal
- 2. Remove numbers
- 3. Remove letters who appeared more than twice in the text.
- 4. Lemmatise the text



Cleaning [17]

COMPARISON OF DEPRESSION INTENSITY SCORE

Text	Symbolic + Sub- symbolic	Sentic API
So alone so tired so bored so ugly so depressed.	0.66375	0.866
Feeling bummed out rn. Family is disappointing and friends are too far away??	0.38461	0.5
Why is it that everyone gets what I want, I guess whatever	0.21962	0.33

RE-EXAMINING THE TOY DATASET

- Time factor
- Lack of annotators from Psychology or Linguistics to give a golden depression score for individual entries in the dataset.
- No way to compare the losses and determine which method (Symbolic + Sub-symbolic or Sentic API) is better in producing the depression intensity score



Warning Sign [20]

O3C TEXT SUMMARISATION (SUBTASK)

TEXT SUMMARISATION (SUBTASK)

Extractive Text Summarisation

- Summarised text appears from their corresponding raw text
- Uses **DeepAl** Text
 Summarisation API
- API call
- Used as a subtask for the emotion-cause pair extraction task

Abstractive Text Summarisation

- Summarised text generates new sentences from the raw texts
- The summarised text might not appear in the corresponding raw text
- Uses Pre-training with Extracted Gapsentences for Abstractive Summarisation (PEGASUS)
- Import PEGASUS libraries from HuggingFace
- Two variant: xsum and reddit tifu

O3D EMOTION-CAUSE PAIR EXTRACTION (ECPE)

INTRODUCTION TO ECPE

Aim: Focus on depressive emotion and the likely cause for it. Then extract the emotion and the cause pair accurately in the context of depression

Clause 1: Adele arrived at her apartment late in the afternoon after a long day of work.

Clause 2: She was still furious with her husband for not remembering her 40th birthday.

Clause 3: As soon as she unlocked the door, she gasped with surprise;

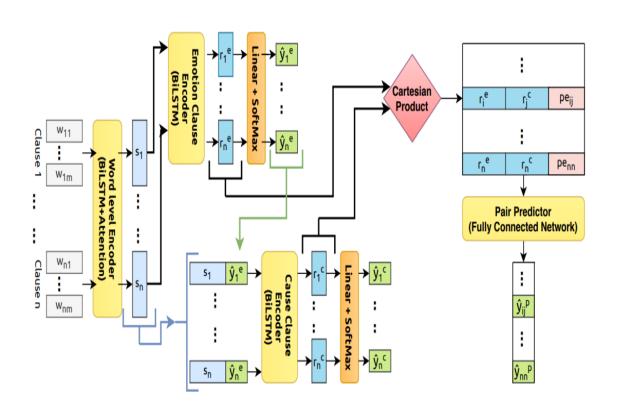
Clause 4: Mikhael and Harriet had organised a huge party for her.

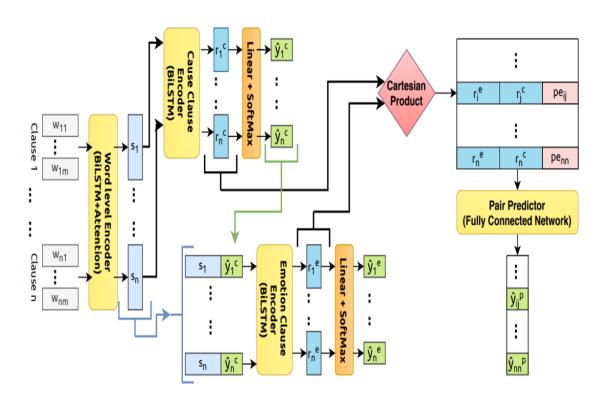
- Above example paragraph contains two emotion-cause pairs
- Clause 2 is an emotion clause (anger) and also the corresponding cause clause (for not remembering her 40th birthday)
- Clause 3 is an emotion clause (surprise)
- Clause 4 is its corresponding clause (organised a huge party for her)

PREVIOUS RESEARCH ON ECPE

- Adopted from "An End-to-End Network for Emotion-Cause Pair Extraction" by A. Singh, S. Hingane, S. Wani, A. Modi et al. (https://arxiv.org/abs/2103.01544)
- Adopting the end-to-end model approach to demonstrate the effectiveness of joint training on the ECPE task
- Benchmark NTCIR-13 workshop dataset is used in their experiment with six emotions
 - Disgust, fear, anger, happiness, sadness and surprise

ARCHITECTURES





E2E-Pext(E) Architecture [21]

E2E-Pext(C) Architecture [21]

PERFORMANCES ON THE NTCIR-13 DATASET

Models	Emotion Extraction (%)			Cause Extraction (%)			Pair Extraction (%)		
	Precision	Recall	F1 Score	Precision	Recall	F1 Score	Precision	Recall	F1 Score
E2E- Pext(E)	71.63	67.49	69.43	66.36	43.75	52.26	51.34	49.29	50.17
E2E- Pext(C)	71.70	66.77	69.10	63.75	42.50	50.42	48.88	48.22	48.37

ADOPTING ECPE IN THIS PROJECT

- Architecture remains mostly the same as the ones used in the research paper, but hyperparameters will be tuned again as the datasets used are different
- Datasets used: Twitter dataset and Reddit dataset
- To perform ECPE in the context of depression

DATA PRE-PROCESSING

- Pre-process data to ensure that the data is presented in separate clauses for the ease of annotation for the emotion and the cause clauses
- The Reddit dataset exists entries with more than 200 clauses, making it computationally expensive for the models to train later
- Reddit data will be summarised using extractive summarisation (subtask) to reduce the number of clauses per text entry



Cleaning [17]

IMPLEMENTATION

- Manual annotation of the emotion and the cause for each of the data entry.
- Instead of six emotions in NTCIR-13, there is only one emotion in the annotated datasets which is labelled as "depressed".



Lightbulb [22]

DATA ANNOTATION & FORMAT

```
77 6
  (6, 4),
1,null,null,My Anxiety Disorder PTSD Depression are real and
2,null,null,today I am battling
3,null,null,My happiness is fading and
4,null,null,my brain is messing with me
5,null,null,so badly I have been trying hard not to cry trying hard just to stay positive
6,depressed,struggling,but I am struggling
```

- 77 6 The data has the index 77 and this piece of data contains 6 clauses
- (6,4) This data's emotion is in clause 6 and the cause is in clause 4
- null This clause does not contain any emotion or cause clause
- depressed, struggling 'depressed' is the clause with the emotion and 'struggling' is the secondary emotion that can be found in the particular clause

MODEL PERFORMANCES

Variant	Dataset	Pair Extraction F1 Scores		
	Twitter	0.5150		
E2E-PExt(E)	Reddit	0.5488		
	NTCIR-13 (benchmark)	0.5017		
	Twitter	0.5089		
E2E-PExt(C)	Reddit	0.5333		
	NTCIR-13 (benchmark)	0.4837		

LIMITATIONS

- Annotating the causes of depression might not be as straightforward as annotating the text as 'depressive' or 'not depressive'
- Bias in annotation making the Pair Extraction F1socre higher or lower than the values presented
- Need for experts to annotate the data but lack of time and cost, resulting in a compromise



Warning Sign [20]

04 FUTURE WORK

FUTURE WORK

- Model deployment on a website or phone application
- Additionally, a 'report' button can be created to inform the relevant authorities to take immediate and appropriate actions to prevent the worsening of one's depression



Future [23]

THANK YOU

REFERENCES

- [1] https://www.pikpng.com/pngvi/xxhxbT_depressed-silhouette-depression-vector-clipart/
- [2] https://neilpatel.com/blog/essential-social-media-metrics/
- [3] https://pngimg.com/image/96242
- [4] https://www.pinclipart.com/pindetail/Tmomow_png-file-yes-and-no-icon-clipart/
- [5] https://www.pinclipart.com/pindetail/xxmxwo_emotion-icon-packs-vector-svg-psd-emotions-png/
- [6] https://www.dreamstime.com/illustration/hiding-behind-mask.html
- [7] https://www.pngkey.com/detail/u2q8r5w7q8w7r5u2_form-application-test-clipboard-check-list-tasks-audit/
- [8] https://www.dreamstime.com/illustration/hiding-behind-mask.html
- [9] https://pngable.com/png/cbPnJ24rnz/data-analysis-integration-png
- [10] https://www.flaticon.com/free-icon/data-storage-stack-variant_31623
- [11] https://www.pngitem.com/middle/oiTomw_step-1-data-cleansing-and-mining-data-cleaning/
- [12] https://colah.github.io/posts/2015-08-Understanding-LSTMs/
- [13] https://towardsdatascience.com/how-to-fine-tune-bert-transformer-with-spacy-3-6a90bfe57647
- [14] https://www.crunchbase.com/organization/deepai
- [15] https://sentic.net/api/
- [16] https://icon-icons.com/icon/pytorch-logo/169823
- [17] https://www.pngitem.com/middle/JxmoJT_transparent-cleaning-icons-png-cleaning-icon-png-png/
- [18] https://toppng.com/idea-png-idea-icon-free-PNG-free-PNG-Images_177239
- [19] https://favpng.com/png_view/question-mark-image-clip-art-information-png/cBueJnxf
- [20] https://www.clipartmax.com/middle/m2i8G6b1Z5m2N4b1_portable-network-graphics-wikipedia-limitations-icon-png/
- [21] https://arxiv.org/pdf/2103.01544.pdf
- [22] https://www.clipartmax.com/middle/m2i8i8m2G6H7Z5d3_evaluate-business-idea-innovation-concept-implementation-innovation-icon/
- [23] https://www.flaticon.com/free-icons/future

Q&A