How good algorithms are to tell us the rating of drugs?

Story about a data miner's exploration in the NPL world

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Introduction

- Online user reviews in the pharmaceutical industry contain valuable real-life collective information about the drug's effectiveness and side effects.
- Because of the diversity and complexity of review data, precisely extracting sentiment information from them is still a challenge.
- Both lexicon + rule-based algorithms and machine learning algorithms have been applied in this area.

Task Overview

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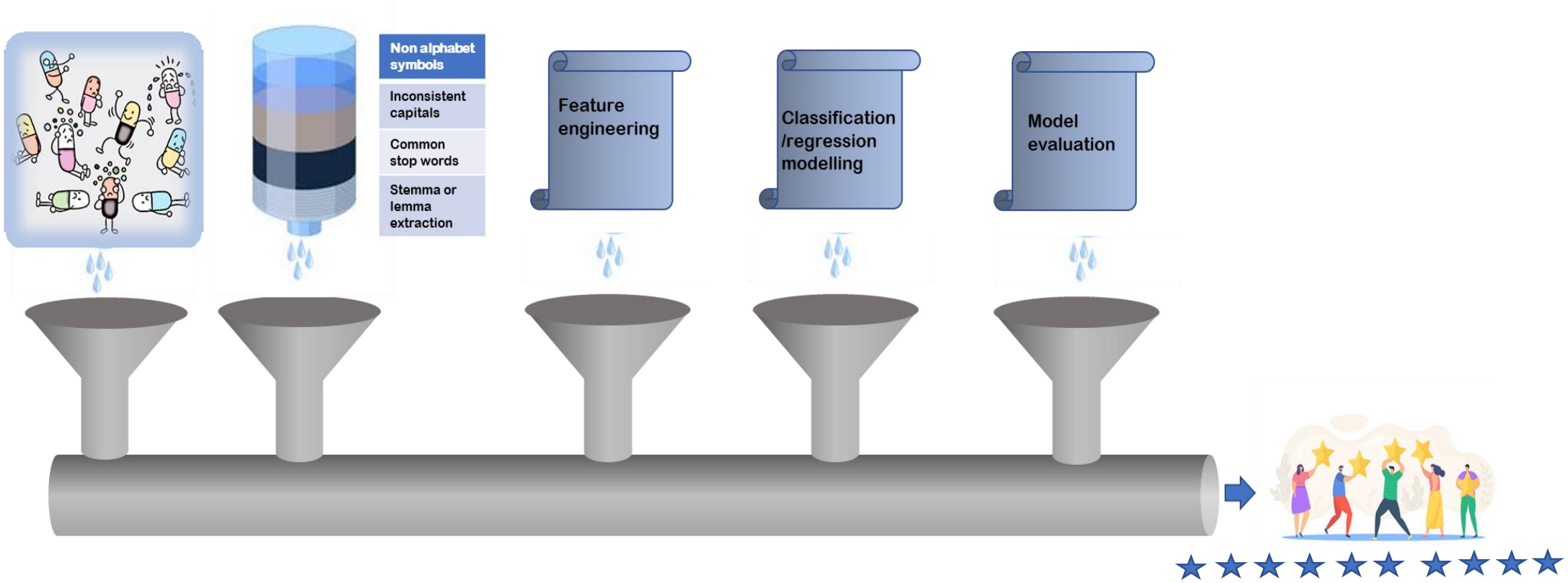
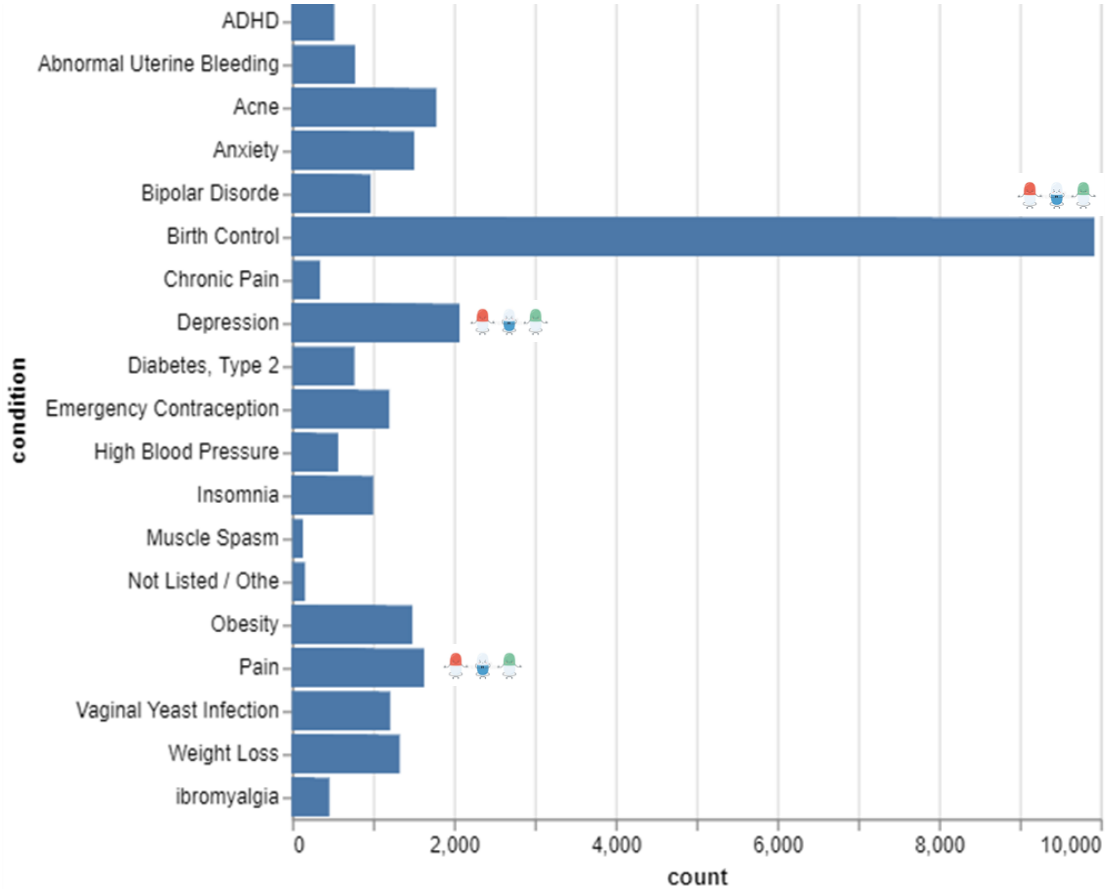
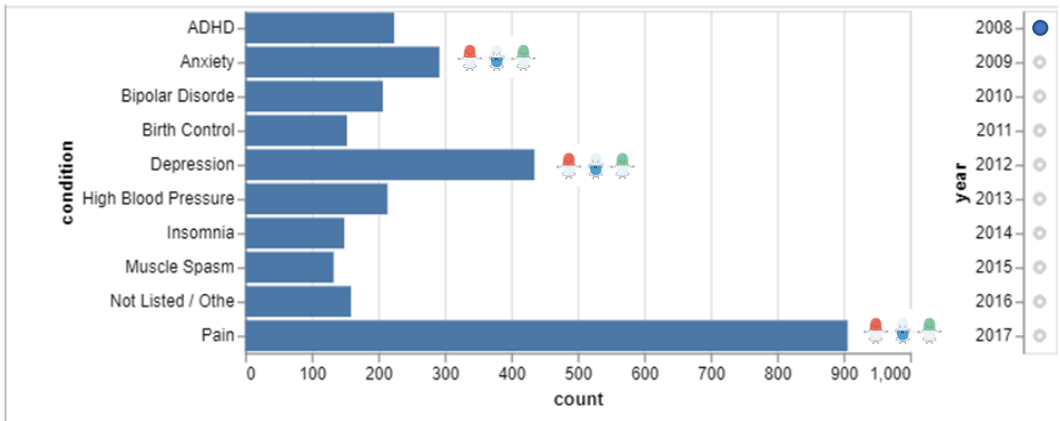
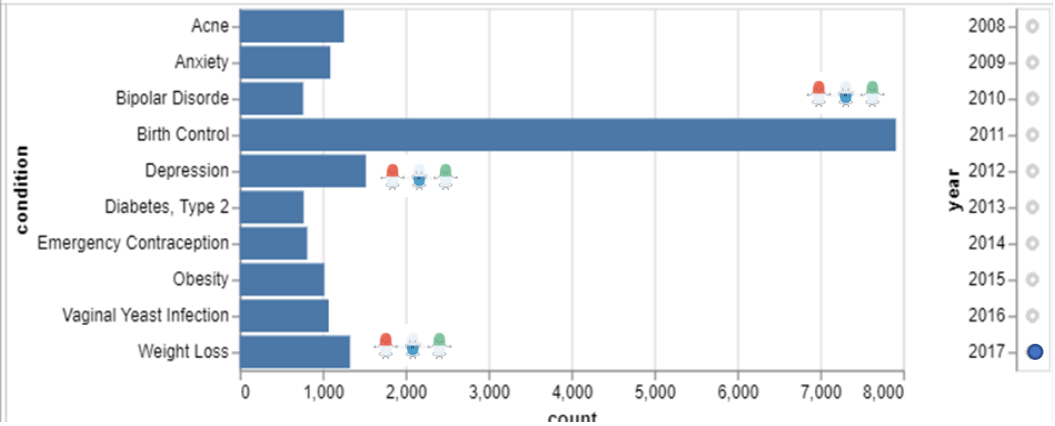


Q1. What does this data tell us?

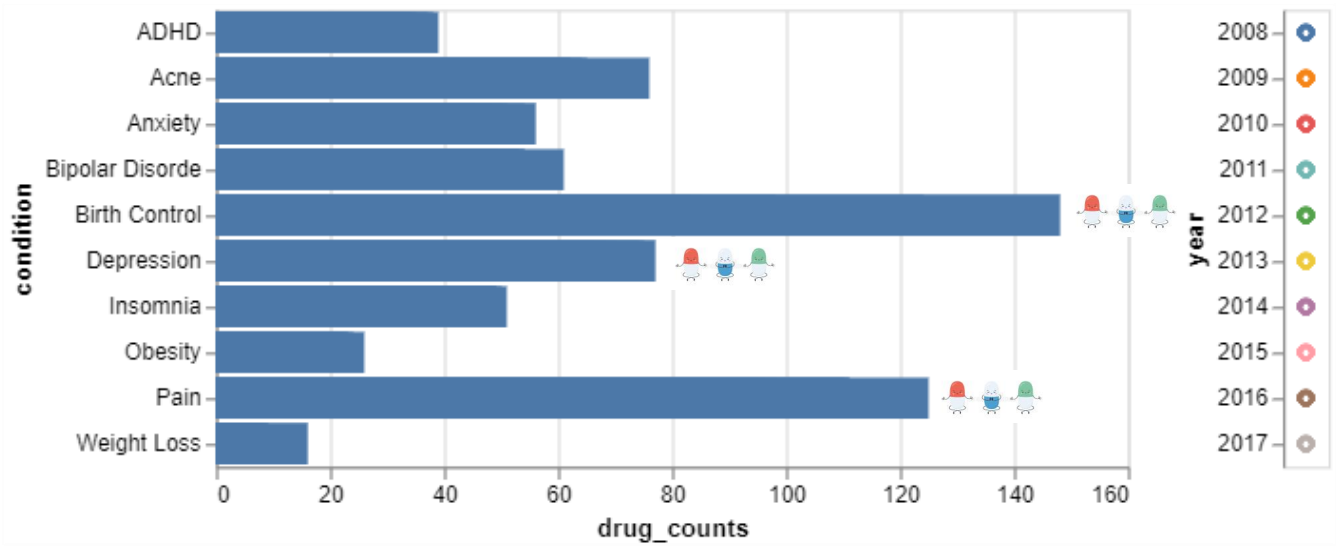
Review N of the Top 10 conditions (916 in total)

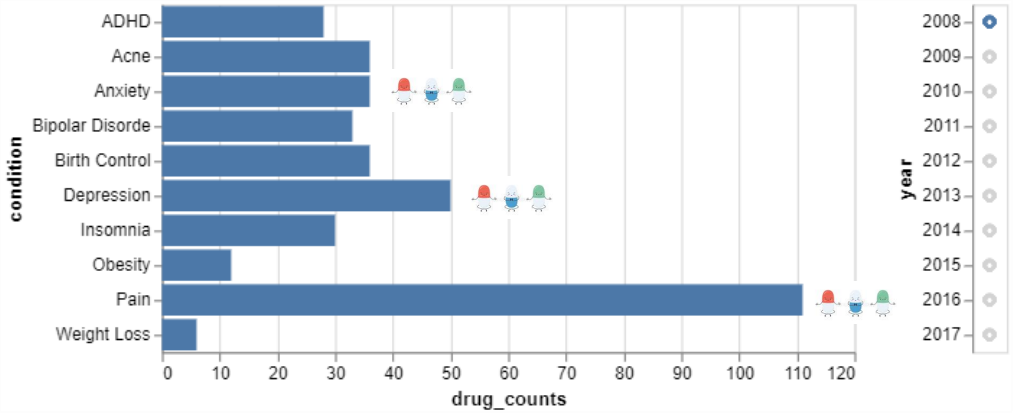


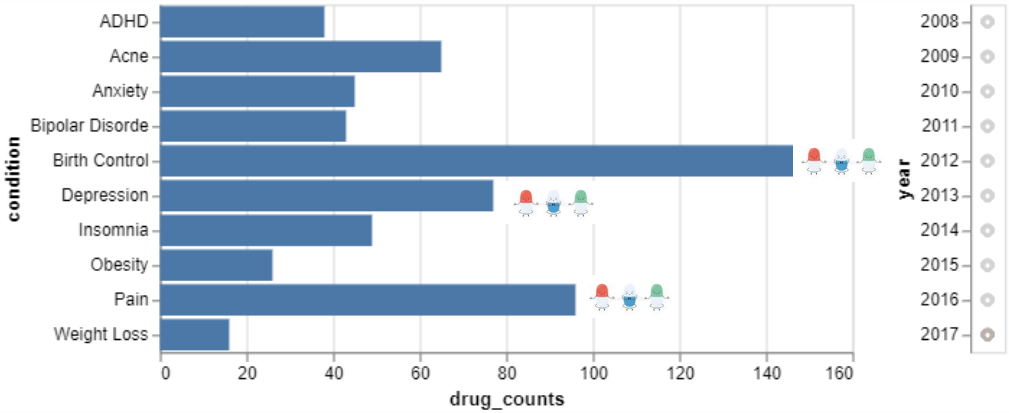




Number of Drugs & Conditions & Year







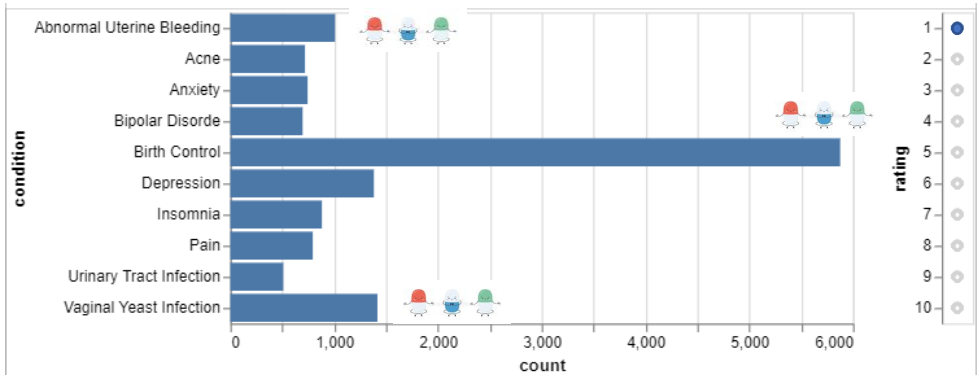
Drug Names & Conditions

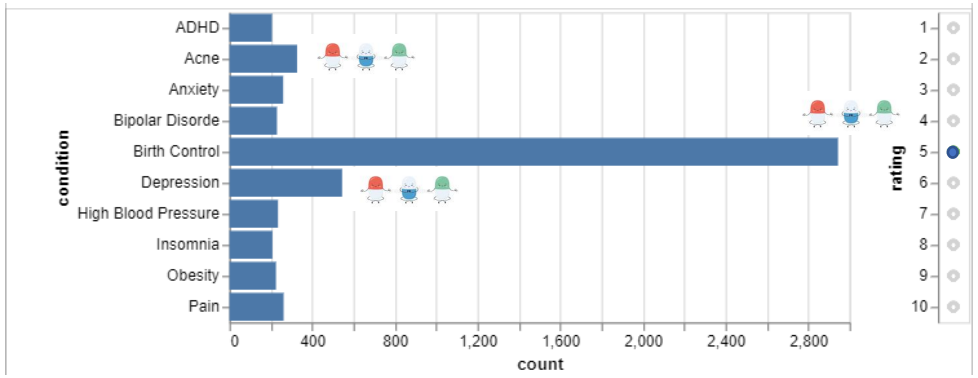
drugName	condition	review	rating
Bupropion	ADHD	72	72
	Anxiety	75	75
	Bipolar Disorde	41	41
	Depression	747	747
	Major Depressive Disorde	142	142
	Migraine Prevention	2	2
	Not Listed / Othe	5	5
	Obesity	6	6
	Panic Disorde	10	10
	Persistent Depressive Disorde	4	4
	Postural Orthostatic Tachycardia Syndrome	2	2
	Premenstrual Dysphoric Disorde	3	3
	Seasonal Affective Disorde	14	14
	Sexual Dysfunction, SSRI Induced	38	38
	Smoking Cessation	199	199

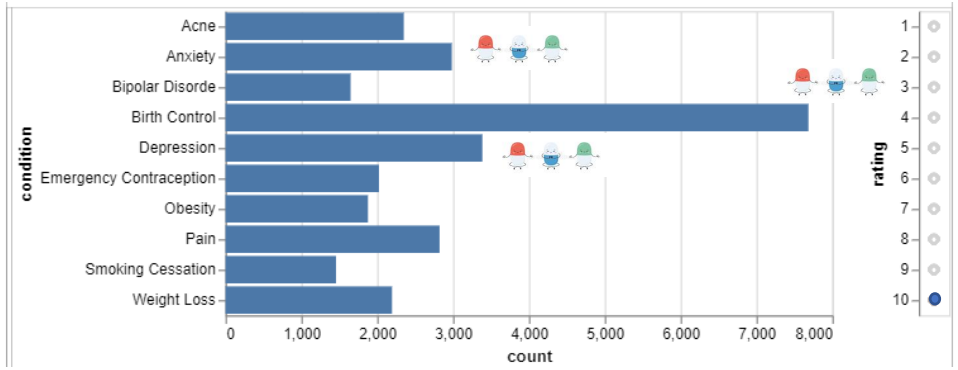
condition	drugName
ADHD	Adderall
	Adderall XR
	Adzenys XR-ODT
	Amantadine
	Amphetamine
	Amphetamine / dextroamphetamine
	Aptensio XR
	Armodafinil
	Atomoxetine
	Budeprion XL

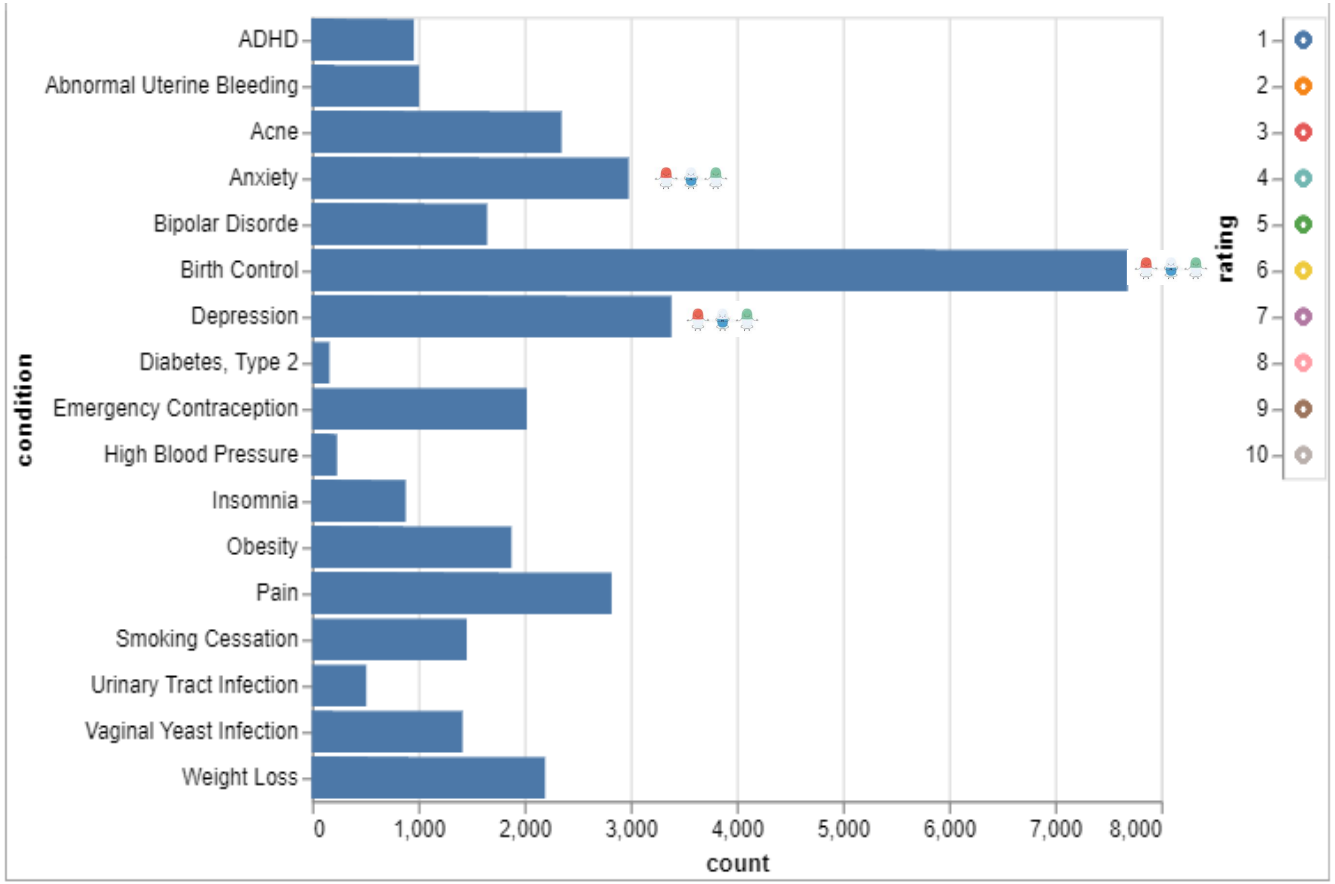
One drug can be applied for multiple conditions. One condition can be treated by multiple drugs. There are totally 3667 drugs in this data set.

Ratings & Conditions

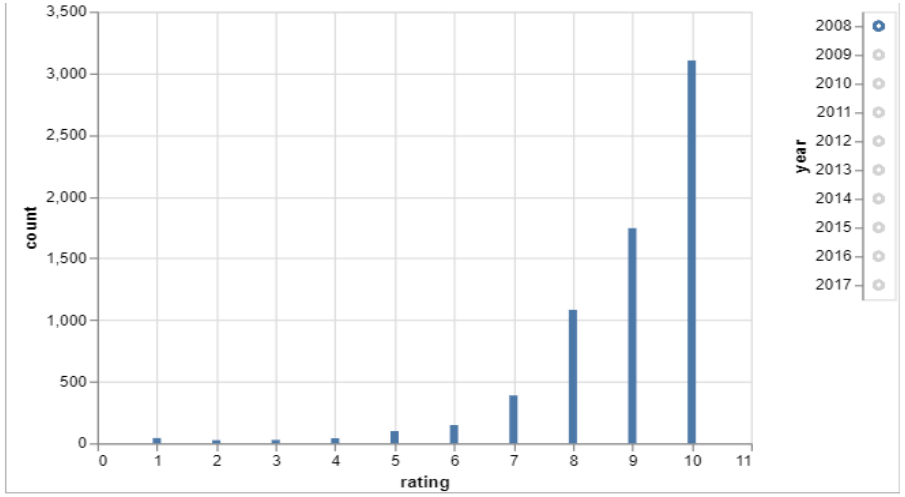


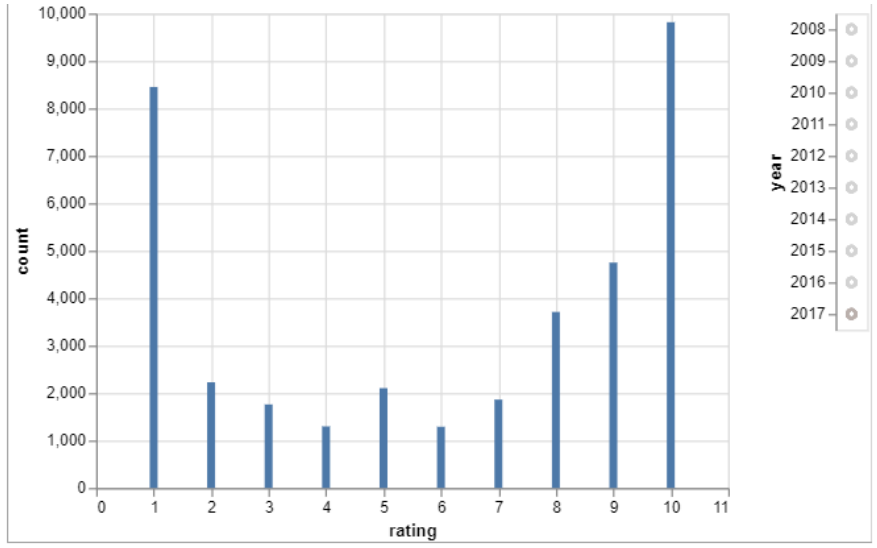


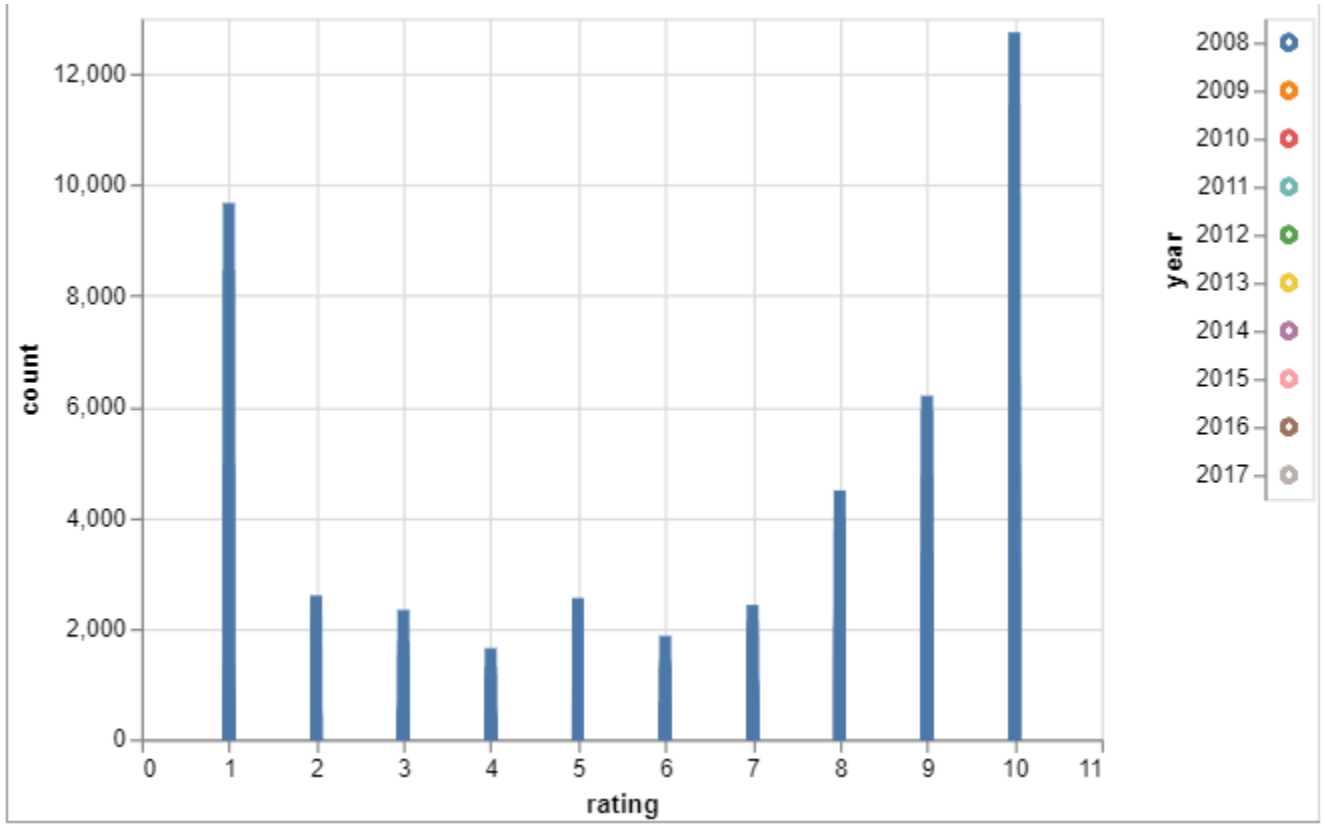




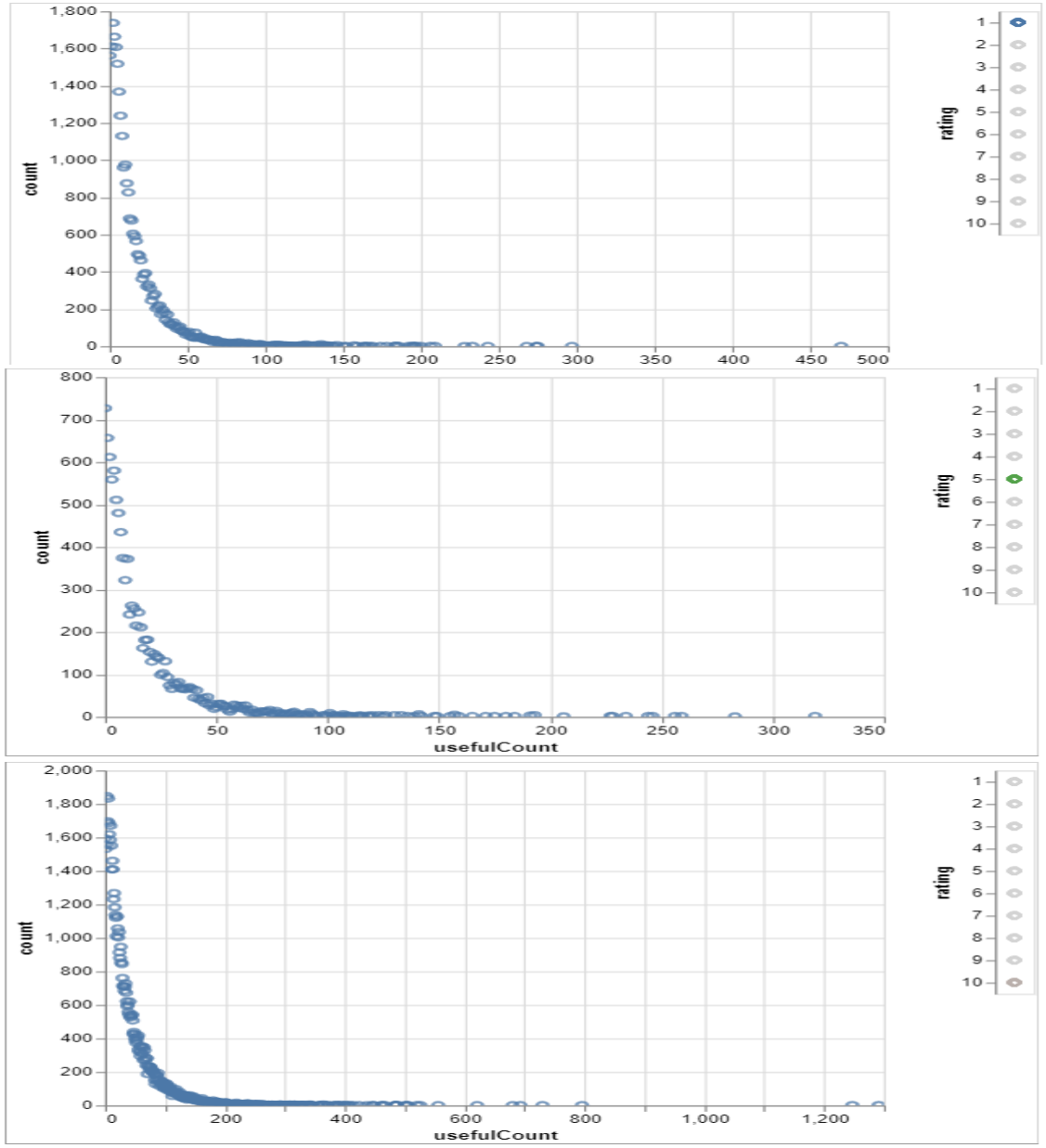
Ratings & Years

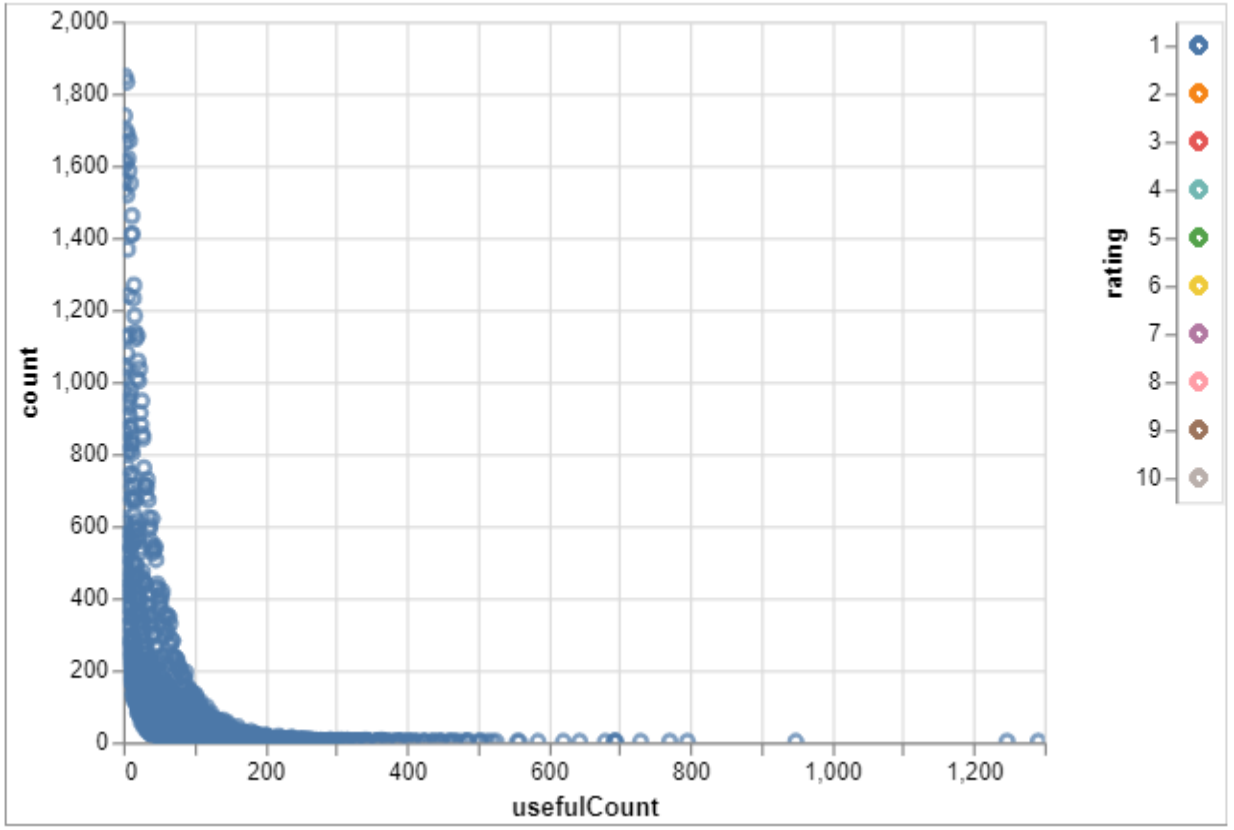






Ratings & Useful Count





Reviews: Word Cloud for Pain Relievers as an Example (unigram)

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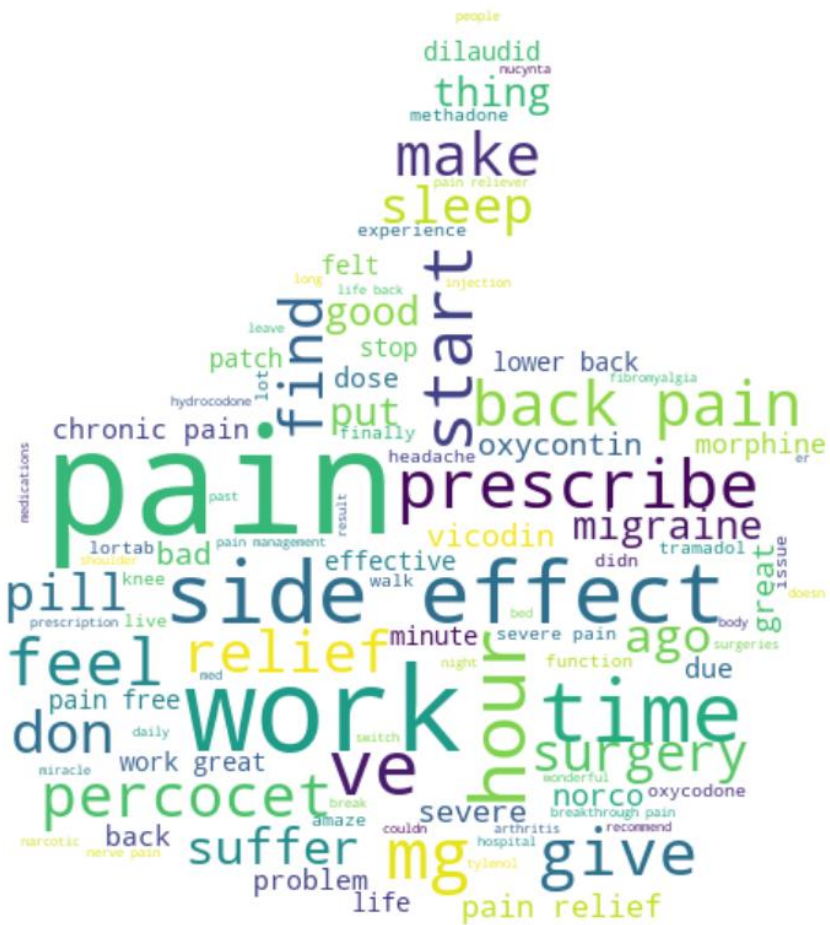
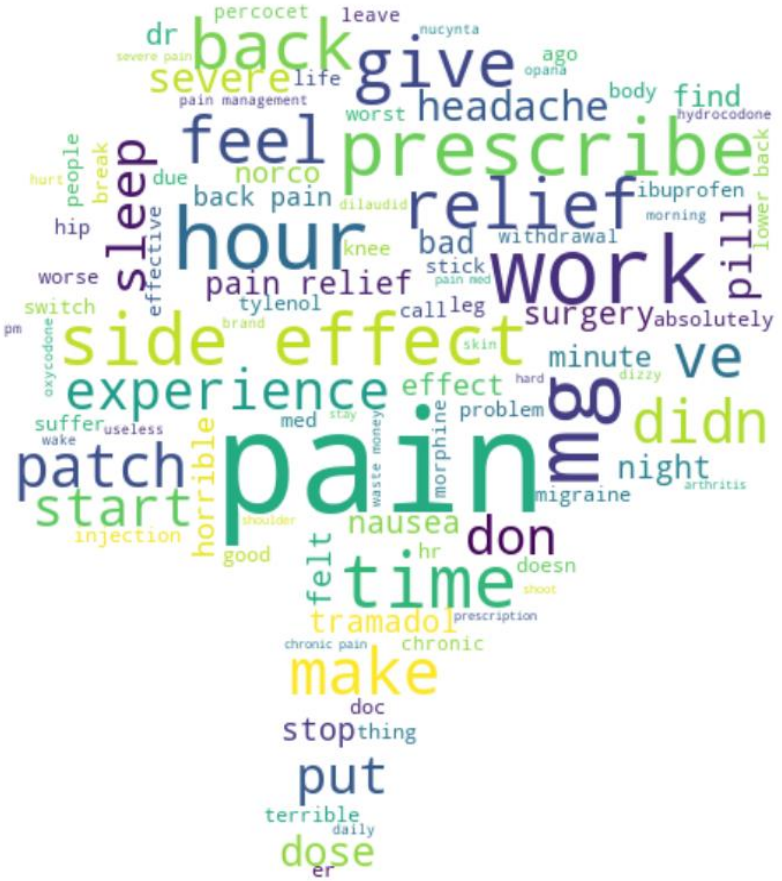
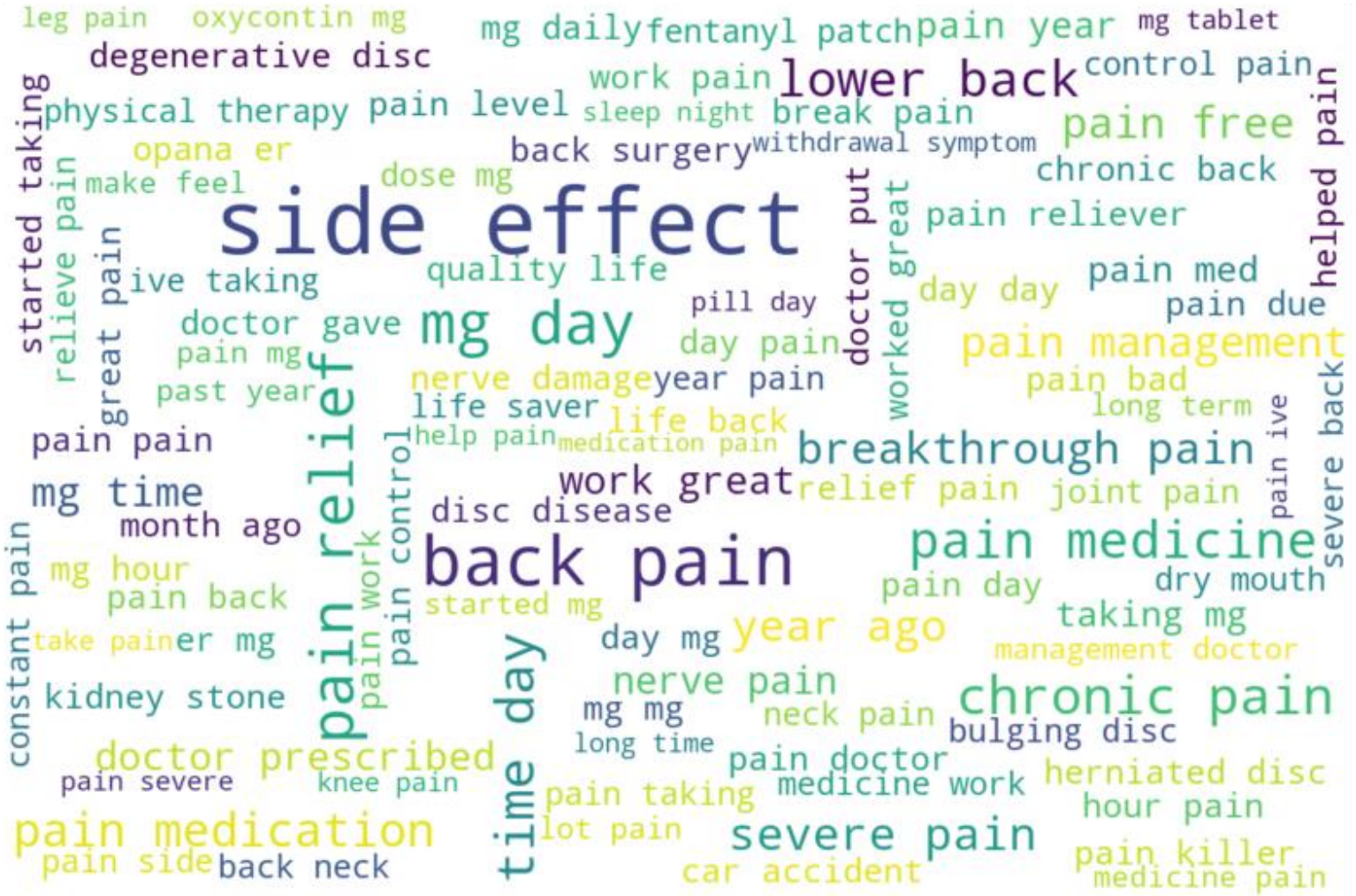




Reviews: Word Cloud for Pain Relievers as an Example (bigram)



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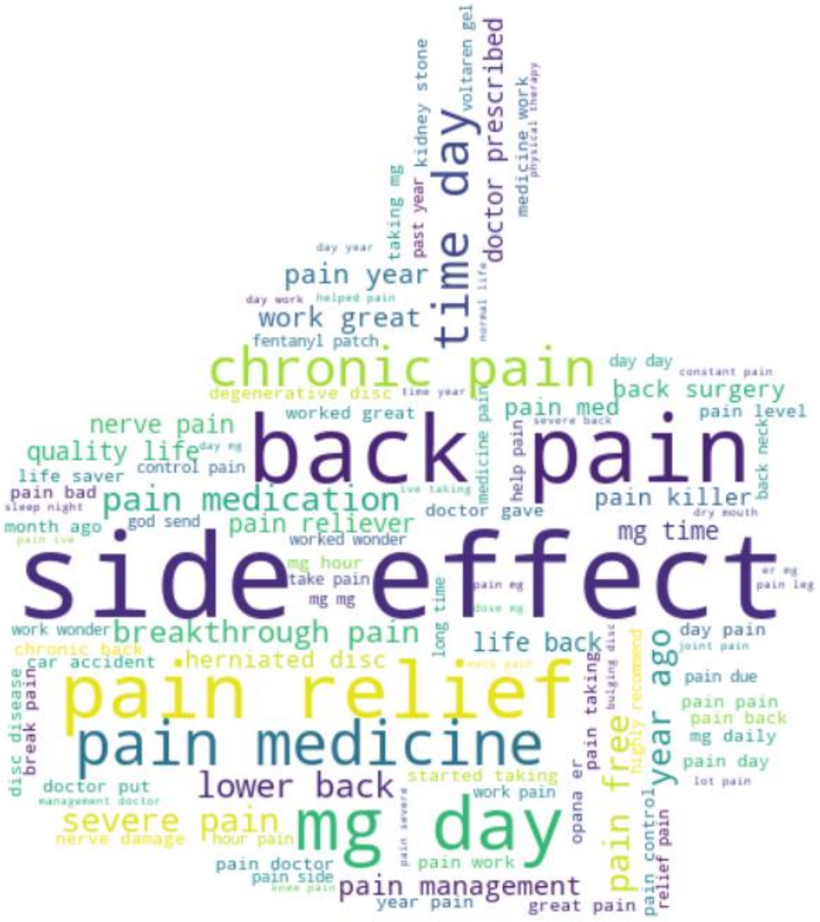
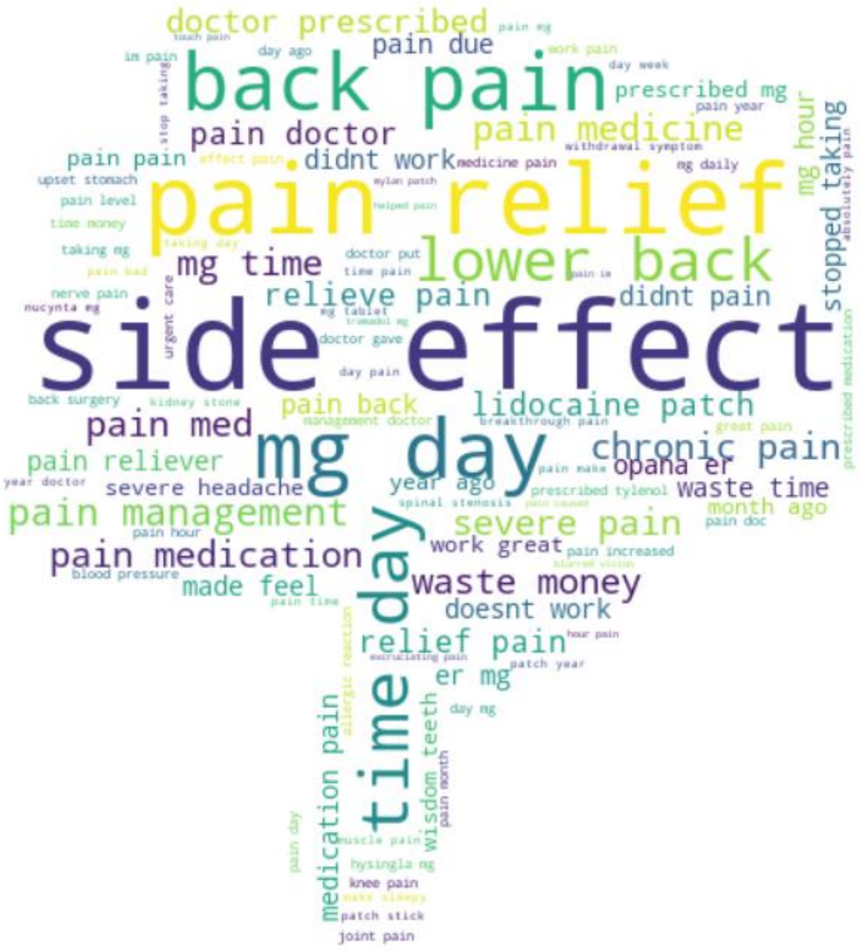
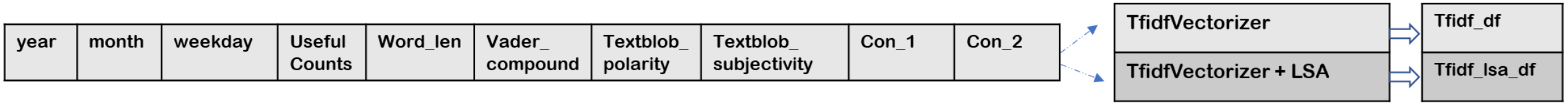


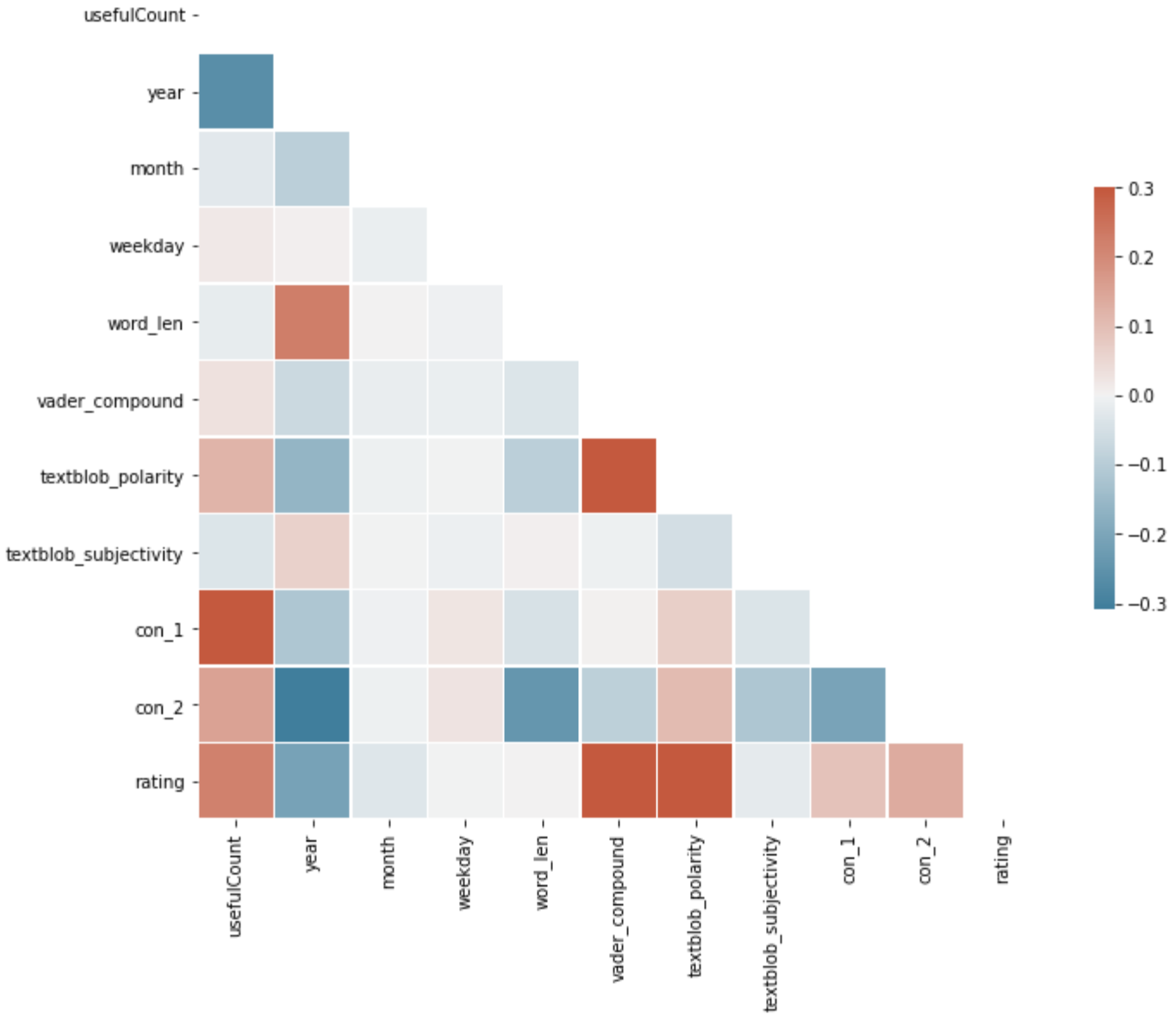


Q2: How can we extract useful features from the data for modeling?💡

- Choose the top 3 conditions data for modeling, birth control, pain and depression. Convert condition into dummy variables.
- Extract year, month and weekday from datetime.
- Extract word length of the reviews as features
- use VADER, to get the sentiment indicator as features
- use TextBlob, to extract sentiment information as features
- Use TfidfVectorizer transform review to get 288 new features. Combine these features with the original features to form tfidf_df
- Use Latent sematic analysis (LSA) to extract information from the review to get 100 new features. Combine these features with the original features to get tfidf_lsa_df

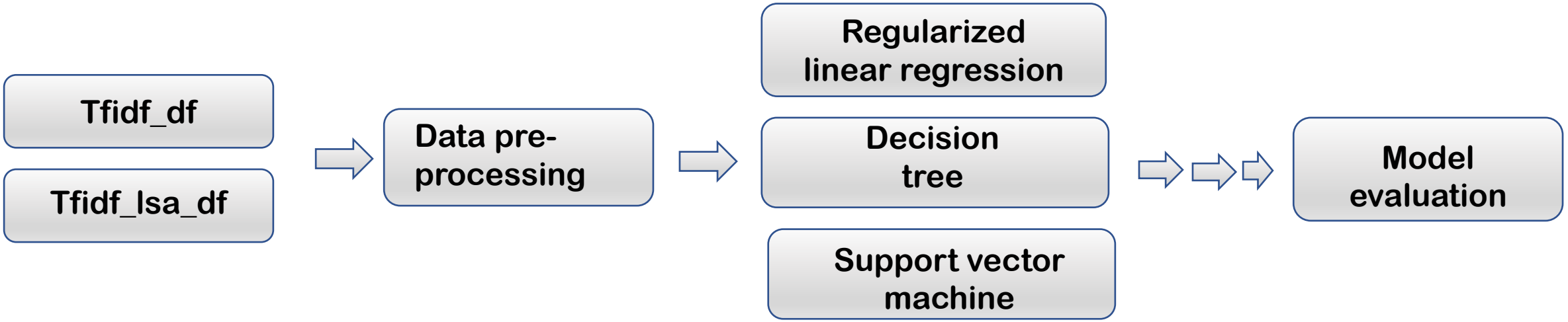


Feature Engineering: correlations between features



Q3: Should we develop regression model or classification model?💡

Regression Model

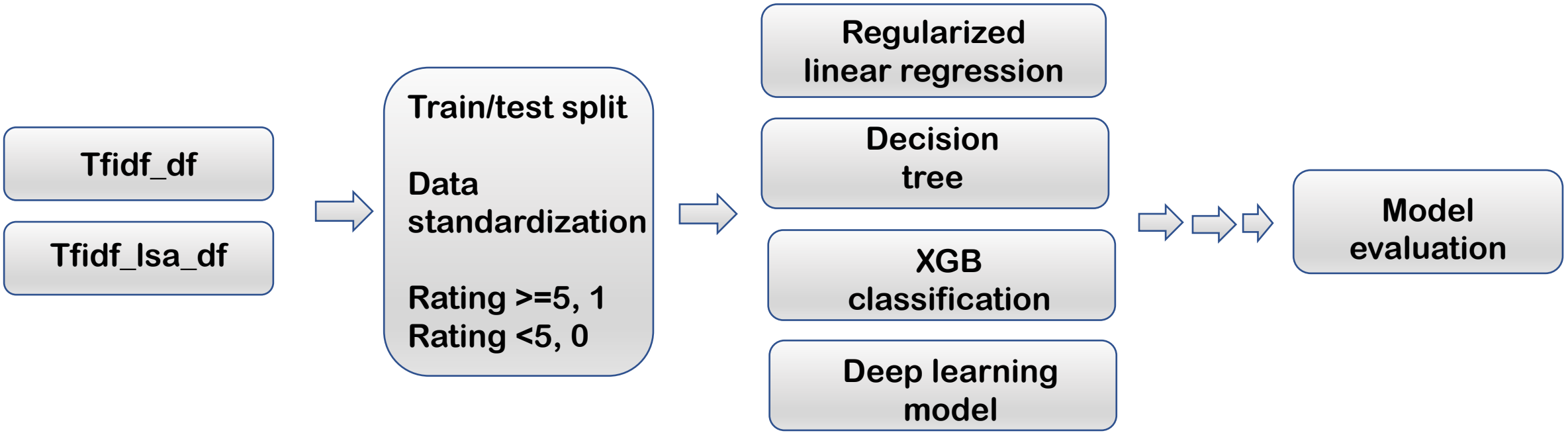


Regression model

Data	Algorithms	Run time	hyperparameter	MSE	MAE	R^2
Tfidf_df	Regularized linear regression	159	Alphas, L1_ratios	6.12	1.99	0.43
	Decision tree	97	Max_depth	5.03	0.97	0.53
	Support vector machine	1908	Default setting	6.12	1.99	0.43
tfidf_lsa_df	Regularized linear regression	51	Alphas, L1_ratios	6.38	2.04	0.40
	Decision tree	140	Max_depth	5.18	0.98	0.52
	Support vector machine	735	Default setting	6.38	2.04	0.40

Q3: Should we develop regression model or classification model?💡

Classification Model



Classification model

Data	Algorithms	Hyper-parameter	Accuracy	Precision	F1 score	Recall	AUC
Tfidf_df	Regularized logistic regression	C	0.809	0.837	0.869	0.903	0.867
	Decision tree	Criterion, Max_depth	0.788	0.82	0.855	0.894	0.817
	XGBoosting	Gamma, subsample, n_estimator, max_depth	0.919	0.934	0.943	0.953	0.953
	Deep learning	N/A	0.907	0.935	0.933	0.932	N/A
tfidf_lsa_df	Regularized logistic regression	C	0.806	0.832	0.867	0.905	0.856
	Decision tree	Criterion, Max_depth	0.809	0.842	0.868	0.896	0.818
	XGBoosting	Gamma, subsample, n_estimator, max_depth	0.926	0.933	0.948	0.964	0.971
	Deep learning	N/A	0.837	0.875	0.885	0.896	N/A

Q4. Conclusion?

- We don’t suggest to develop regression model considering the long run time for all algorithms.
- Classification model can give us decent results
- Tfidf + LSA produced features can give us comparable results as tfidf alone engineered features.
- XGBoosting is the best performer among all tested algorithms
- Deep learning models didn’t give us surprise in this case.

Q5. What do you want to improve if given more time? 💡

- Develop more comprehensive models including all conditions in the original data instead of only 3 in this case.
- Optimize the hyperparameters in deep learning models and test their performance again.
- Develop web application to give the predicted results directly to the stakeholders.
- Try auto training and fast deployment for state-of-the-art NLP models on Hugging Face

Summary: 💡 💡 💡 💡 💡

- Science is driven by curious and persistent people.
- Data science is driven by critical thinking and curiosity.
- What's your driving force to overcome obstacles and conquer what you couldn't in your data science journey?