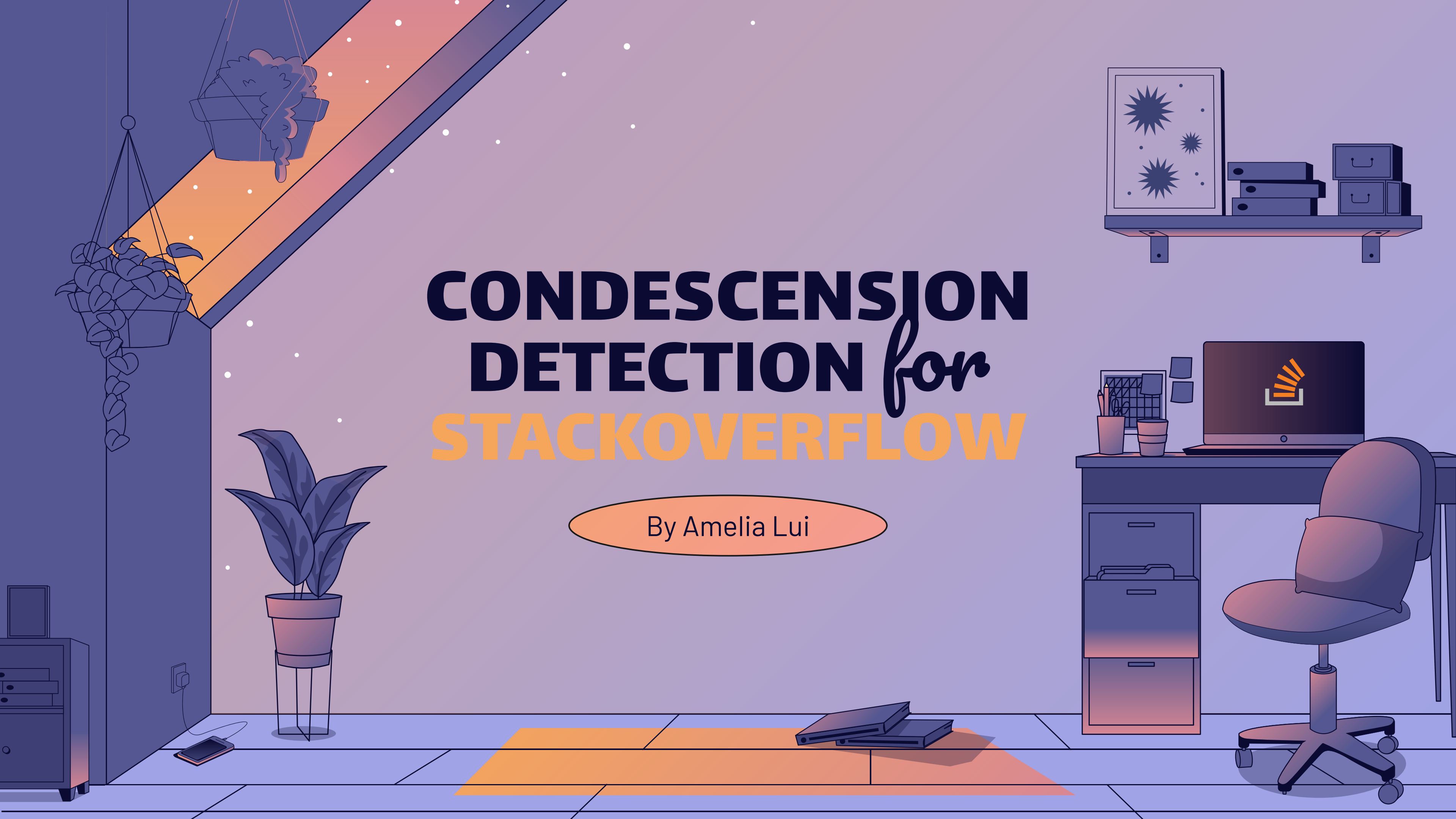

CONDESCENSION DETECTION *for* STACKOVERFLOW

By Amelia Lui

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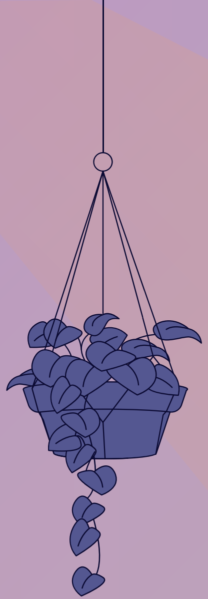

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INTRODUCTION

What is StackOverflow?
Motivation and Objective

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METHODOLOGY

Data, tools,
models, evaluation

03

RESULTS

Visualizations,
Findings, Model Performance

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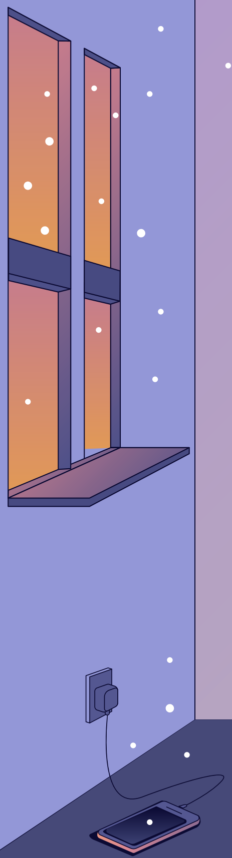
CONCLUSION

Application,
Future Work

01

INTRODUCTION

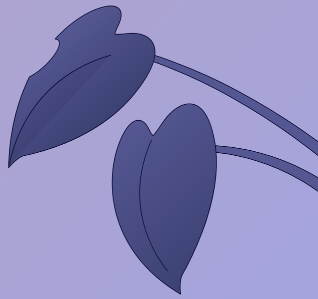
- **What is StackOverflow?**
- **Motivation**: A kinder, more productive learning experience
- **Goal**: Classify a comment as condescending or not condescending



02

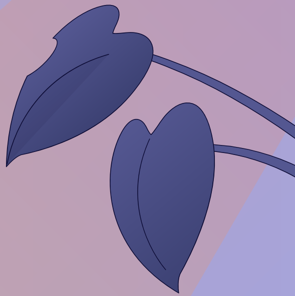
METHODOLOGY

- **Data**: Stack Overflow Data from Kaggle
- **Tools**: Numpy, Pandas, Matplotlib, Seaborn, Sklearn, Vader, nltk, scipy, gensim
- **Topic Modeling**: LSA, NMF
- **Classification**: kNN, Logistic Regression, Random Forests
- **Model Evaluation**: emphasis on recall, but with context of confusion matrix



03

RESULTS: topics



Latent Semantic Model

TOPIC ONE

use, code, would, question, answer, like, think, c, also, need, want, using, time, get, work, example, could, mean, say, see, know, much

TOPIC TWO

jpeg, ocaml, postgresql, words, case-insensitive, -tiers, n-tiers, associative, foo, controlchars.quote, age, href=, cryptography

TOPIC THREE

asked, good, perfectly, accepted, answered, correct, subjective, post, voted, help, yes, wrong, upvote, google, original

03

RESULTS: topics

Latent Semantic Model

1: Further Questions

use, code, would, question, answer, like, think, c, also, need, want, using, time, get, work, example, could, mean, say, see, know, much

2: Technical

jpeg, ocaml, postgresql, words, case-insensitive, -tiers, n-tiers, associative, foo, controlchars.quote, age, href=, cryptography

3: Reviewing Comments

asked, good, perfectly, accepted, answered, correct, subjective, post, voted, help, yes, wrong, upvote, google, original

03

RESULTS: *topics*

Non-negative Matrix Factorization

TOPIC ONE

mean, string, new, example, different, best, statement, name, read, work, say, get, words, foo, syntax, var, f, x, file, variable, upvote, phrase

TOPIC TWO

code, use, would, think, like, c, need, time, way, want, could, good, method, get, function, c++, type, object, say, example, better

TOPIC THREE

question, answer, asked, good, one, answers, would, valid, c++, ask, vote, perfectly, accepted, nice, different, wrong, better

03

RESULTS: topics

Non-negative Matrix Factorization

TOPIC ONE

mean, string, new, example, different, best, statement, name, read, work, say, get, words, foo, syntax, var, f, x, file, variable, upvote, phrase

TOPIC TWO

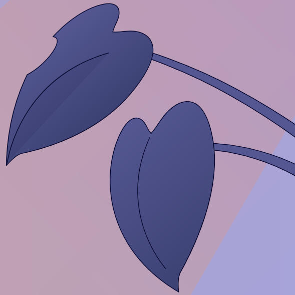
code, use, would, think, like, c, need, time, way, want, could, good, method, get, function, c++, type, object, say, example, better

TOPIC THREE

question, answer, asked, good, one, answers, would, valid, c++, ask, vote, perfectly, accepted, nice, different, wrong, better

03

RESULTS: topics



Final Model: Latent Semantic Model w/ TF-IDF

1: Further Questions

use, code, would, question, answer, like, think, c, also, need, want, using, time, get, work, example, could, mean, say, see, know, much

2: Technical

jpeg, ocaml, postgresql, words, case-insensitive, -tiers, n-tiers, associative, foo, controlchars.quote, age, href=, cryptography

3: Reviewing Comments

asked, good, perfectly, accepted, answered, correct, subjective, post, voted, help, yes, wrong, upvote, google, original

03

RESULTS: classification

Baseline Model

Let this model predict the *majority class* every time

accuracy score: 89.07%

precision score: 0.00%

recall score: 0.00%

f1 score: 0.00%

03

RESULTS: *classification*

Final Model

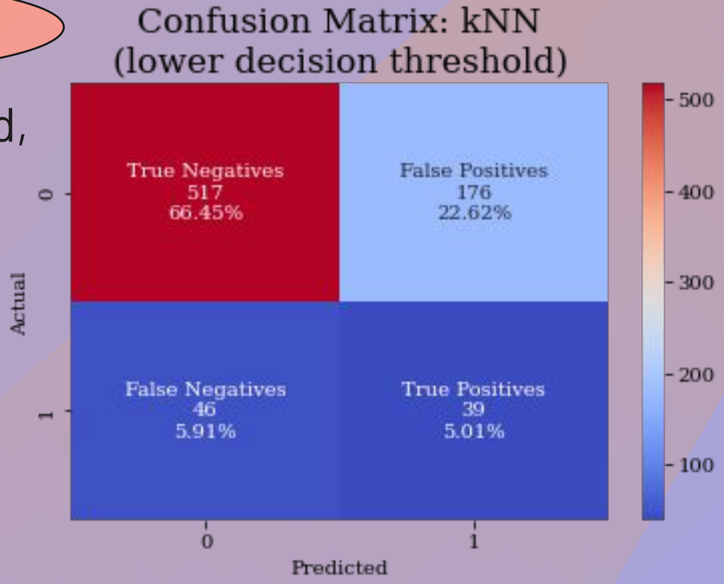
kNN (k=3), with upsampled, scaled data and lower decision threshold

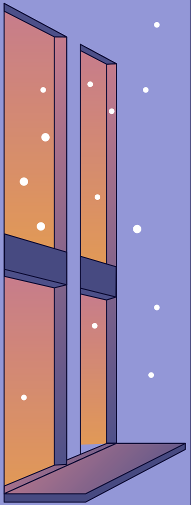
accuracy score: 71.47%

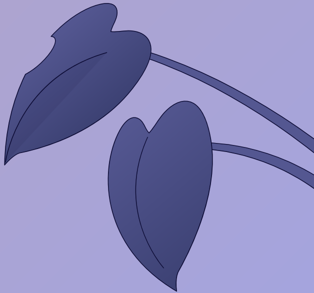
precision score: 18.14%

recall score: 45.88%

f1 score: 26.00%



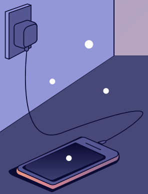


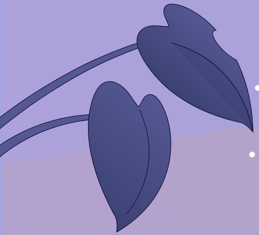


02

CONCLUSION

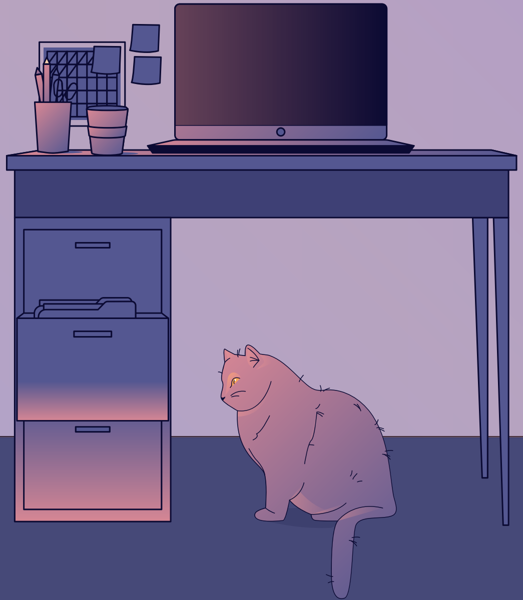
- **Application**
  - Place warning to choose words more kindly if comment detected as condescending
- **Further Work**:
  - Get rid of technical terms
  - Look at other classification model
  - More data

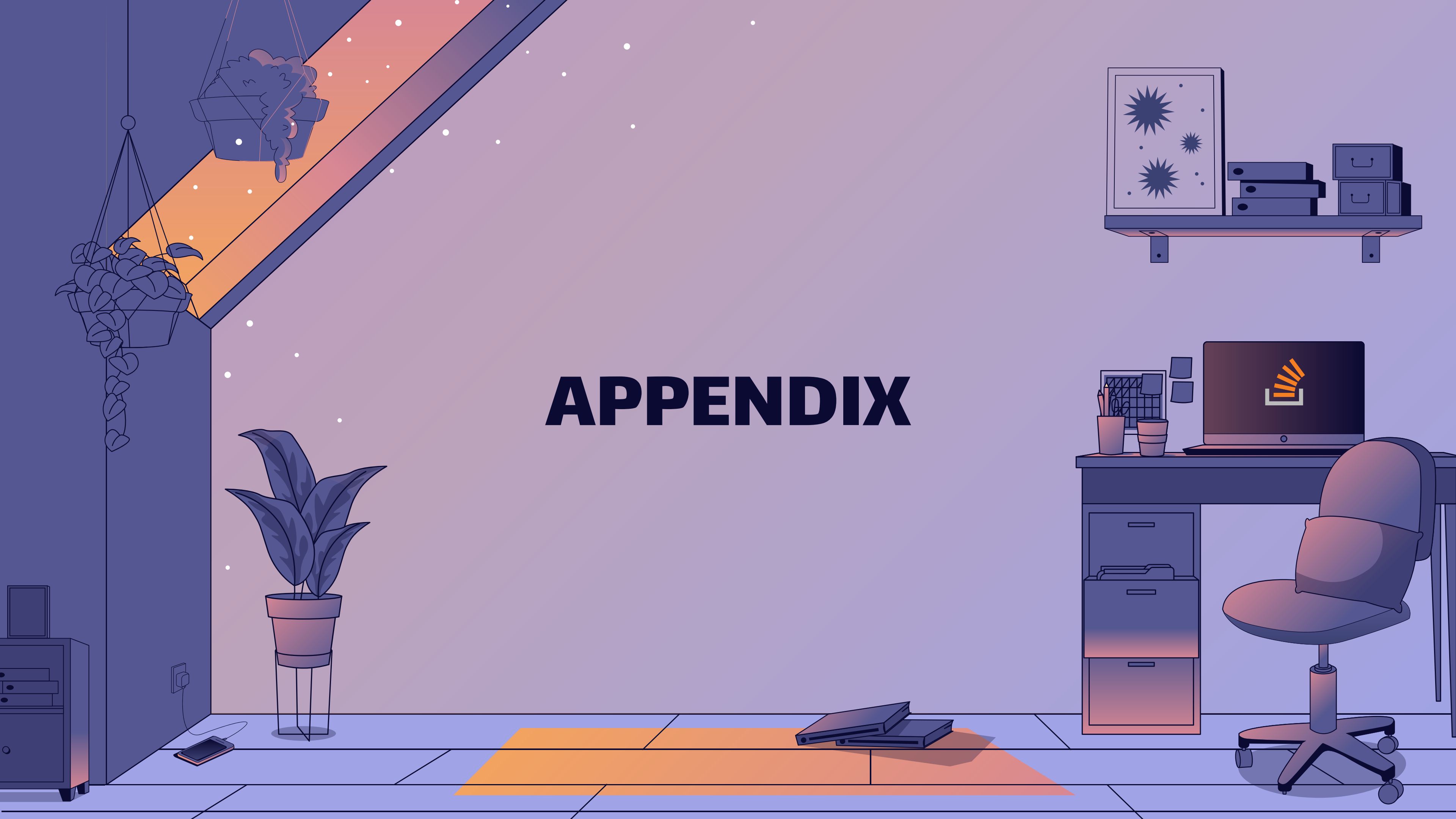




Thank You!

Slides by Slidesgo





APPENDIX

Funny condescending comments hall of fame (from tedious data labelling)

sensible human brains are becoming a rarity these days

if you're ever even tempted to use it, quit engineering now

Your co-workers are going to hate you

And if you purchase that domain I will never be able to look at you the same way again

kNN (k=3)

accuracy score: 74.55%

precision score: 14.01%

recall score: 25.88%

f1 score: 18.18%

Logistic Regression

accuracy score: 10.93%

precision score: 10.93%

recall score: 100.00%

f1 score: 19.70%

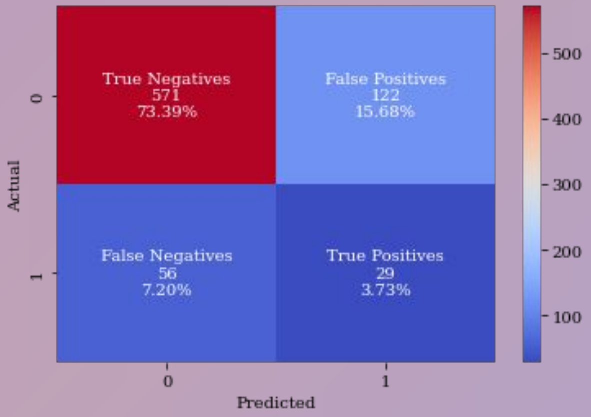
Random Forests

accuracy score: 86.25%

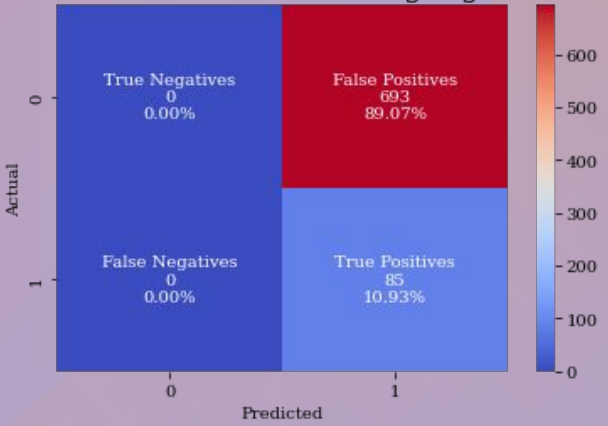
precision score: 15.62%

recall score: 5.88%

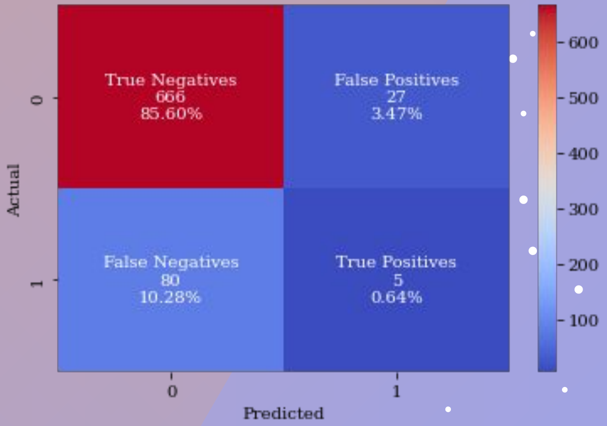
f1 score: 8.55%



Confusion Matrix - kNN



Confusion Matrix - LogReg



Confusion Matrix - Random Forests

For easy comparison of classification models performance (before lowering decision threshold)

kNN (k=3)

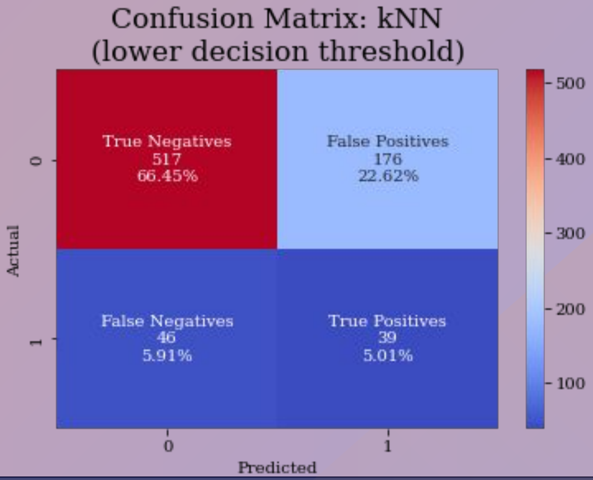
accuracy score: 71.47%

precision score: 18.14%

recall score: 45.88%

f1 score: 26.00%

Final model



Logistic Regression

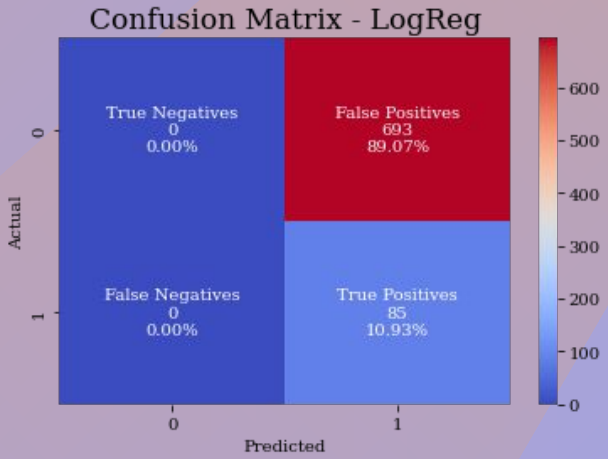
accuracy score: 10.93%

precision score: 10.93%

recall score: 100.00%

f1 score: 19.70%

Same results



For easy comparison of classification models performance (after lowering decision threshold)