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PROJECT OVERVIEW



Problem Statement

Challenge:

 to predict deal probability for listings on Avito.com, Russia's largest classified advertisement platform

Goal:

 to equip sellers with insights to optimize listings and help the platform to improve user experience

Data Summary

Scope

- 1.5M listings in March 2017
- Tabular, text, image data

Target Variable

deal_probability

Challenge

- Tabular mostly categorical
- Russian text
- Large size (50GB+ images)

Methodology

Multi-modality

- Text embeddings with TF-IDF, SpaCy, FastText and images embeddings with ResNet 50
- SVD dimensionality reduction

Stacking Ensemble

 Combine outputs from base models across data modalities



(TABULAR) FEATURE ENGINEERING



Original Features	Price Statistical Features	Text-Related Features	Combination Features	
region	category_price_mean	title_length	region_city	
city	category_price_std	description_length	all_category	
parent_category_name	category_price_skew	title_word_count	category_param_1	
category_name	city_price_mean	description_word_count	region_category_user	
param_1	city_price_max	title_has_keyword	city_category_user	
param_2	city_price_skew	description_has_keyword		
param_3	price_to_category_mean	title_digit_count		
price	price_to_category_max	description_digit_count		
user_type	price_log	description_newline_count		
	price_bin	description_missing		
TOTAL: 9	TOTAL: 10	TOTAL: 10	TOTAL: 5	
TOTAL: 34				

Table 1: Tabular Feature Engineering

- 9 Original Features
- 10 Price Statistical Features
- 10 Text-related Features (length, word count...)
- 5 Combination Features

34

Total Tabular Features into future models



TEXT FEATURE EXTRACTION



- > Extract Embeddings with three different methods
- > Use Singular Value Decomposition (SVD) to reduce dimension

TF-IDF

- TF-IDF, 500 Embeddings
- TF-IDF, Embeddings SVD to 5d

SpaCy

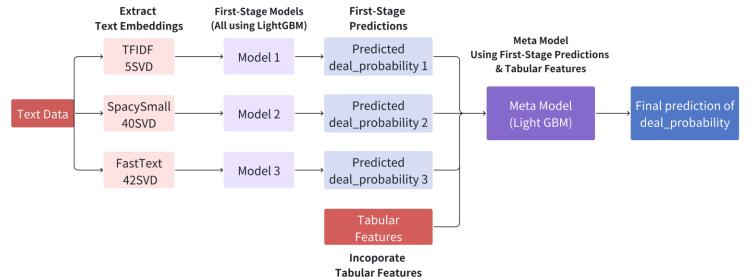
- SpaCy Small Russian, 98
 Embeddings / Medium
 Russian, 300 Embeddings
- SpaCy Small Russian, SVD to 40d / Medium Russian, SVD to 100d

FastText

- FastText trained on our data, Embeddings 100
- FastText trained on our data, SVD to 42d
- Pretrained FastText,Embeddings 300
- Pretrained FastText, SVD to 50d



STACKING MODELS



Stacking Model 1:



SLOAN SCHOOL

- 3 First-Stage Models:
 - TFI-DF, Spacy, FastText Embeddings→
 Predict deal_probability separately
- Meta Model:
 - Combines first-stage predictions and tabular features

Stacking Model 2:

- 2 First-Stage Models:
 - FastText → Predict price
 - Spacy → Predict deal_probability
- Meta Model:
 - Combines first-stage predictions, tabular features, and TFI-DF embeddings

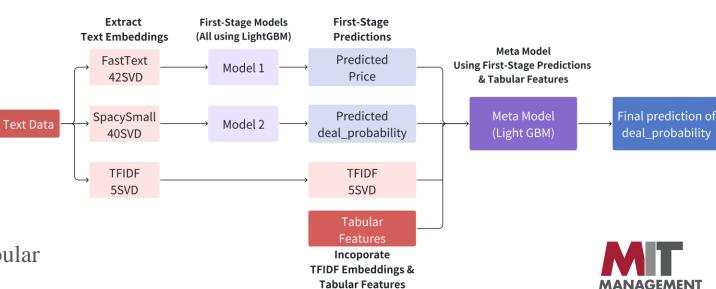


Table 4.1: Summary of Text and Tabular Models Performance in Complete Dataset

Tabular Baseline	.227894



RMSEs when Directly Using Embedding as Features for LightGBM

	SVD Dimension	RMSE - Embedding Only	RMSE - With Tabular	
TF-IDF	5	.252066	.227283	
SpaCy Small	40	.248780	.227110	
SpaCy Medium	100	.246289	.227009	
FastText	42	.235021	.226067	
FastText Pretrained	50	.235337	.227278	I

0.227894

RMSE of Tabular Baseline

6.7%

Average RMSE improvement By combining Tabular and Embeddings Features

RMSEs when Stacking Embedding LightGBM

First-stage Models	Second-stage Model	RMSE
deal_probability ~ SpaCy deal_probability ~ TF-IDF deal_probability ~ FastText	First-stage Preds + Tabular	.226904
<pre>price ~ FastText deal_probability ~ SpaCy</pre>	First-stage Preds + Tabular + TD-IDF	.227119

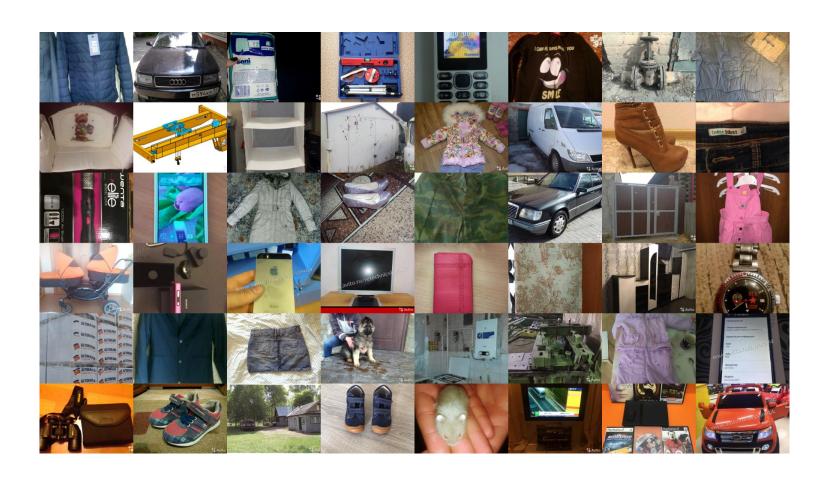
0.226067

RMSE of Best Model



IMAGE FEATURE EXTRACTION





- Visual features matter
 - Important product characteristics, product quality, and buyer interest
 - Majority (93%) of listings has associated image for the listed product
- Images are expensive
 - 50+ GB of image data, not realistic for our computing resources
 - 20% subset of data with images to evaluate image and other features



MODEL PERFORMANCE IN IMAGE SUBSET



Tabular Baseline .232013

.232013
RMSE of Tabular Baseline

RMSEs for Training and Testing Models in Subset for Image Data

	SVD Dimension	RMSE - Embedding Only	RMSE - With Tabular
Text Embedding	42	.241487	.230863
Image Embedding	500	.242552	.230489
Text + Image			.229803

.230489
RMSE of Best Bi-Modality

.229803
RMSE of Tri-Modality



CONCLUSION



- Our experiments demonstrate that
 - Power of multimodality: Inclusion of unstructured data is crucial for improving predicting deal probability of online listings
 - Comparing text models: Neural-network-based text embedding (FastText) outperforms frequencybased embedding (TF-IDF) in this task
 - Complementary power: Inclusion of image features on top of text and tabular models significantly boosted predictive accuracy
- Stacking ensemble
 - Stacking boosted accuracy: Effective in leveraging information from diverse sources

- Some constraints still require future work
 - Feature Engineering: Explore additional engineered features from tabular, text, and image data to enhance predictive performance
 - Advanced Stacking: Incorporate image embeddings alongside text embeddings in firststage models, explore multi-stage stacking, or test new intermediate response variables
 - Scaling Image Analysis: Extend image feature analysis to the full dataset to fully capture the role of visual features in deal probability
 - Model Extensions: Experiment with more advanced architectures for image and text embeddings, such as transformers



