

The background is a dark blue gradient. It features several thick, wavy, light blue lines that flow across the top and bottom of the image. Scattered throughout the background are numerous small, five-pointed stars in white and light blue. The stars are more densely clustered in the top right and bottom left corners.

BUYING FRIENDS?

MODELLING PRO-RUSSIAN VOTING BEHAVIOUR  
IN THE UNITED NATIONS GENERAL ASSEMBLY

DATA SCIENCE PROJECT BY MARIA

# PROJECT OVERVIEW

## Background

Russia's aggressive international behaviour

## Question

What drives other countries to support Russia by voting in line with its interests in the United Nations General Assembly (UNGA)?

## Machine Learning Models

Goal is to identify main features of countries that support Russia in UNGA resolutions

## Hypothesis

A country's economic ties and dependencies on Russia are the strongest predictor of its voting alignment with Russia in the UNGA



# DATA

## Dataset

- 192 rows (based on UN members) and 12 columns
- Self-constructed from different sources (UN voting data, OECD, UNCTAD etc.)

## Target

- **Pro-Russian Voting Index:** continuous values between 0 and 1  
35 UNGA resolutions crucial for Russian foreign policy (Ukraine, Georgia)  
Timeframe 2008–2023, coding: support = 1, against = 0, abstentions/absences = 0.5,  
Index per country based on arithmetic mean (sum values/ number resolutions)

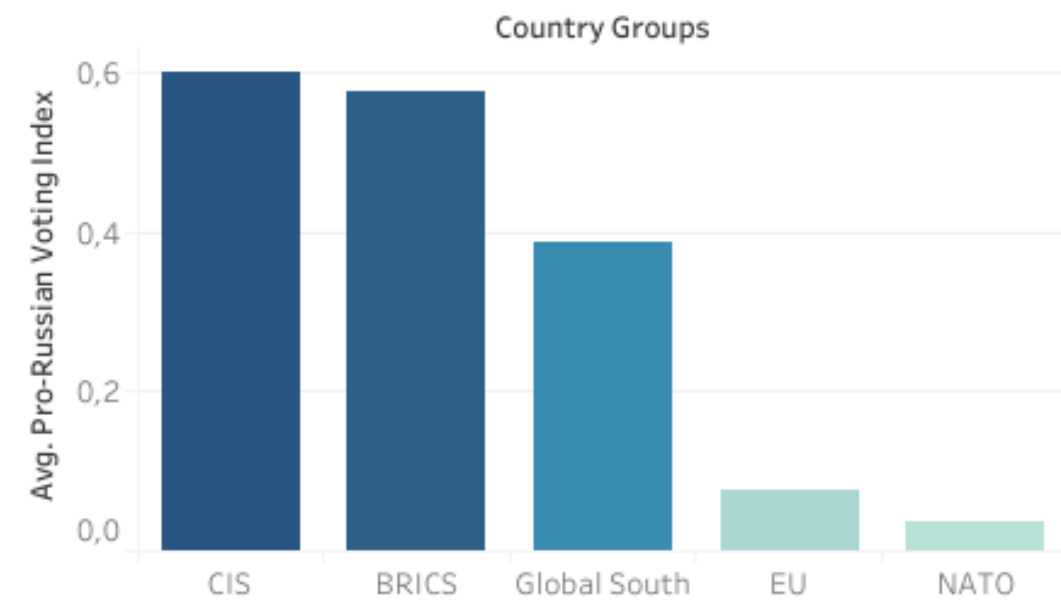
## Features (for each UN member)

- **Economic:** Mean Russian Aid Amount per Year (\$ MM), Bilateral Investment Treaty with Russia (0/1), Export and Import Partner Share with Russia, GDP per capita (\$)
- **Other:** Regime Type (democratic/authoritarian), Distance to Moscow in km, Comecon Membership (0/1), Defense Cooperation Agreement with Russia (0/1), Membership in Organisation with Russia (0/1)

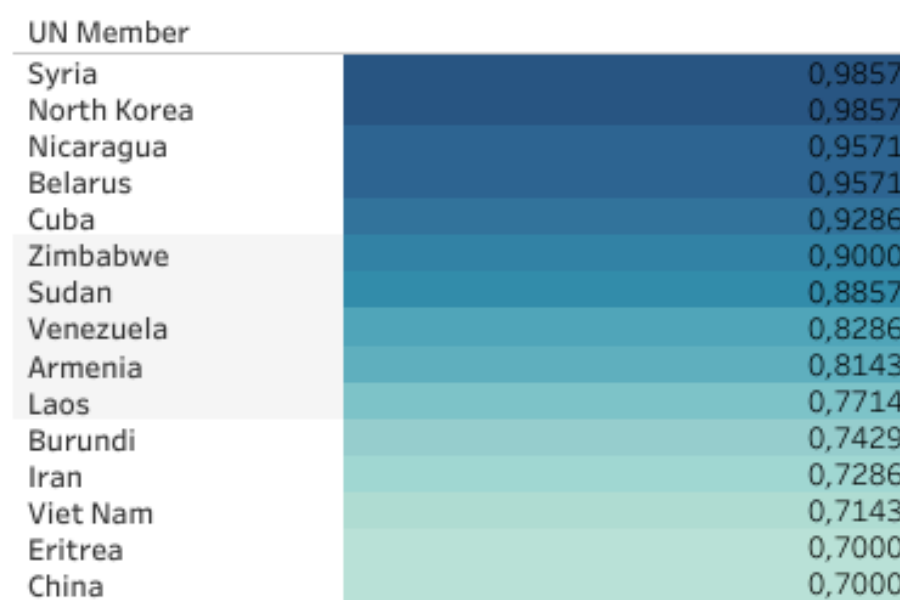
# EXPLORATORY DATA ANALYSIS

## Analysing Pro-Russian Voting Behaviour in the United Nations General Assembly (UNGA)

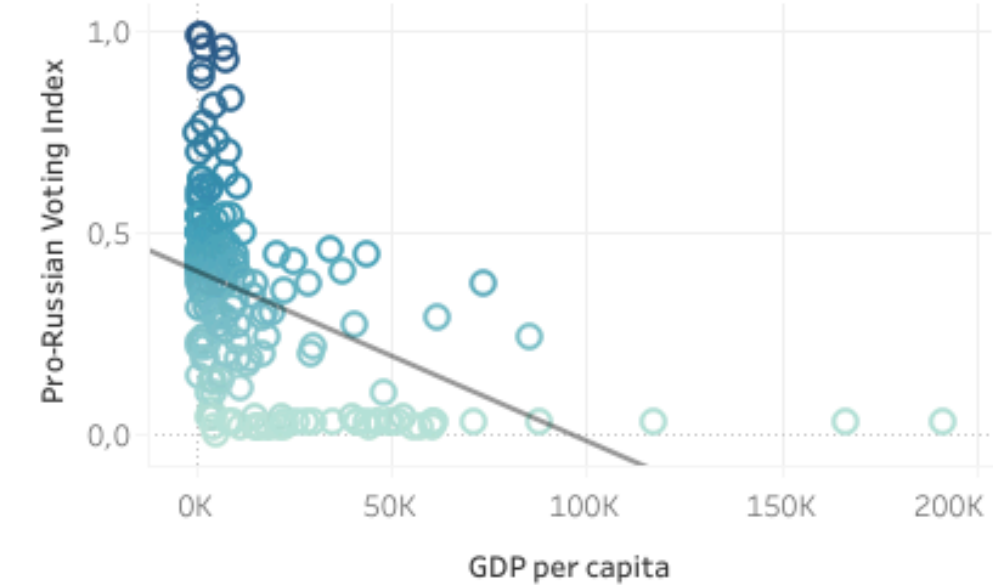
Pro-Russian Voting by Country Groups



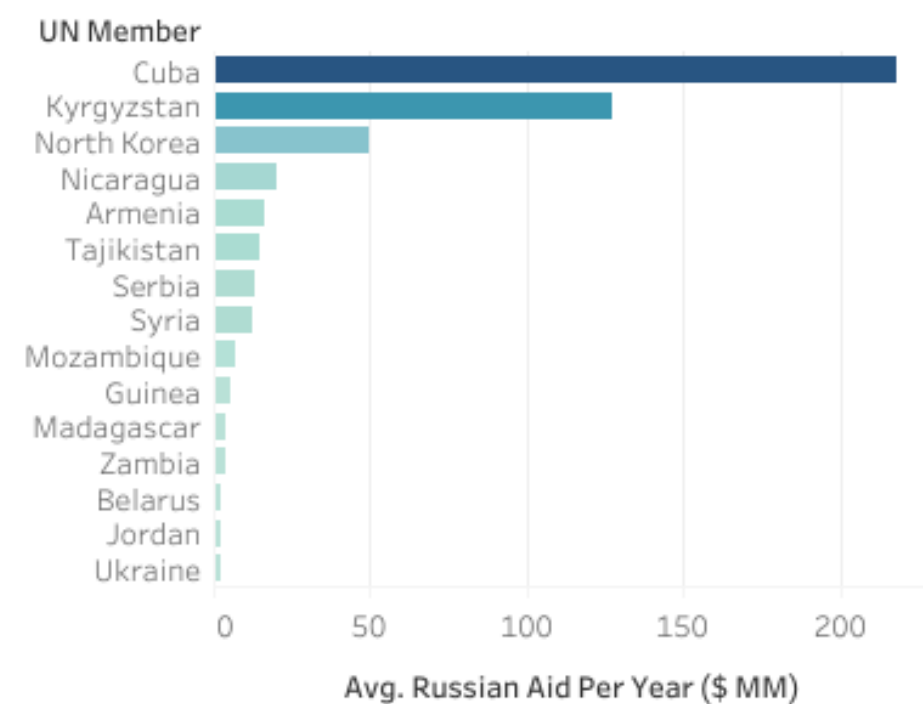
Top 15 Countries by Pro-Russian Voting Index



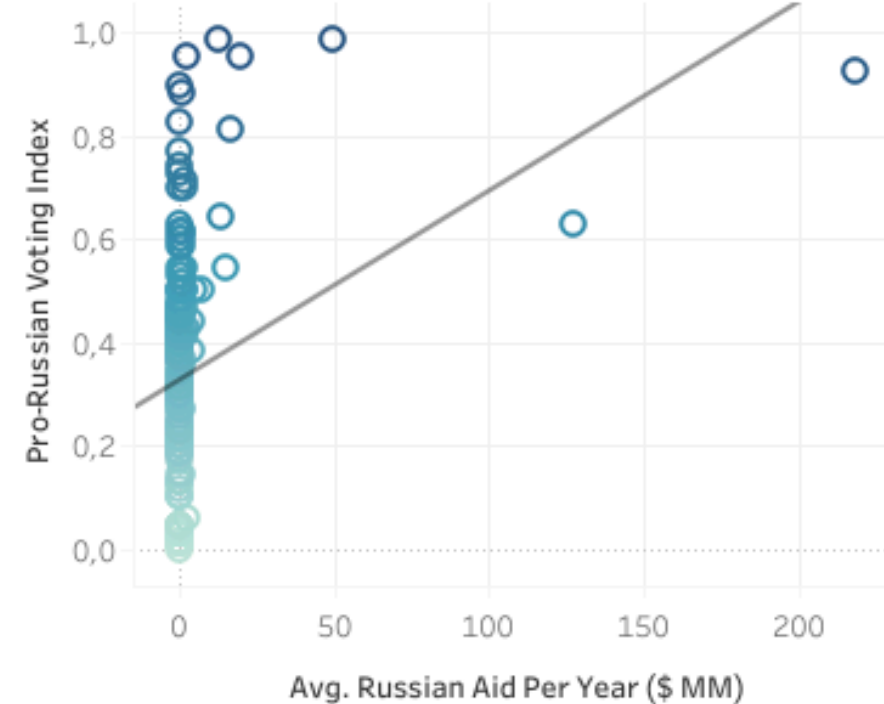
GDP Per Capita vs. Pro-Russian Voting



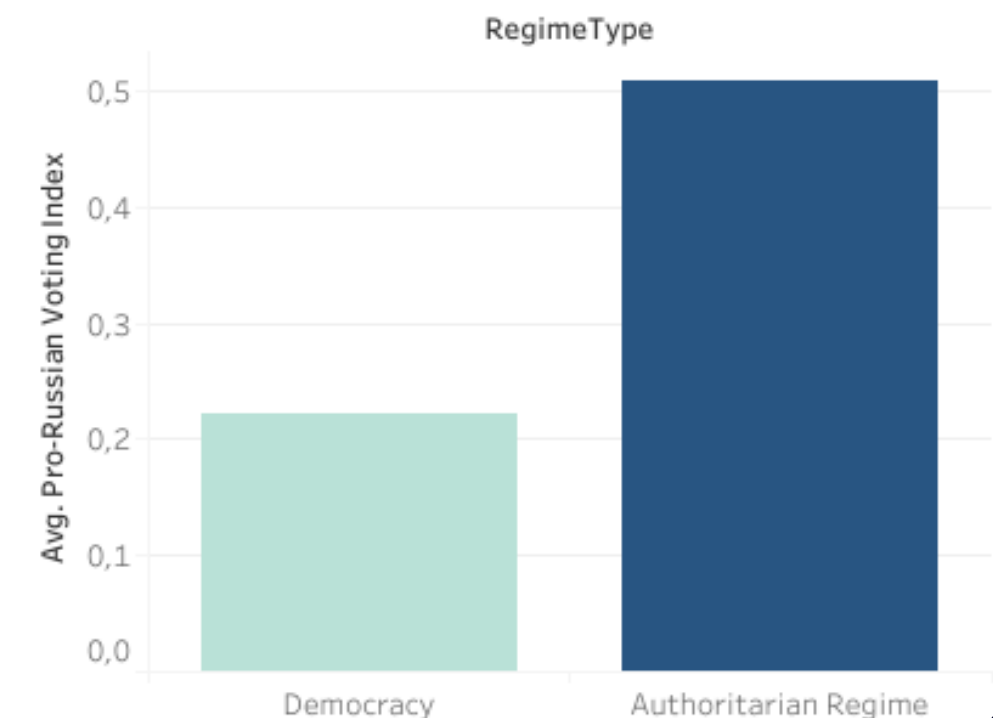
Top 15 Receiver Countries of Russian Aid



Receiving Russian Aid vs. Pro-Russian Voting



Average Pro-Russian Voting by Regime Type



# DATA PREPARATION

## Problem

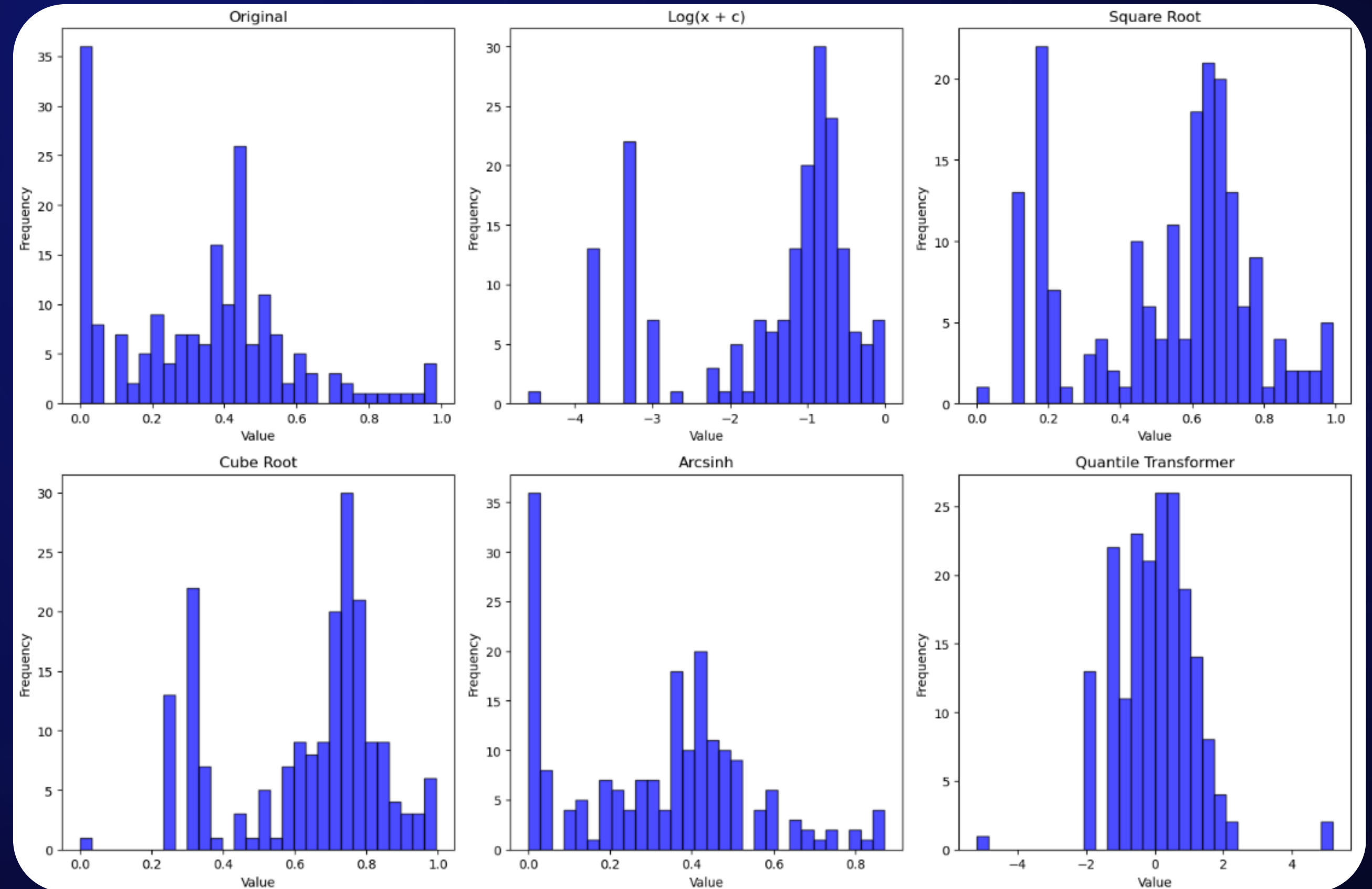
- Target Pro-Russian Voting Index not normally distributed

## Solution

- Quantile Transformer most normal distribution

## Trade-Off

- Predictions can be back-transformed but coefficients not interpretable in original scale anymore



# FEATURE SELECTION & ENGINEERING

## Low Correlation with Target $< 0.1$

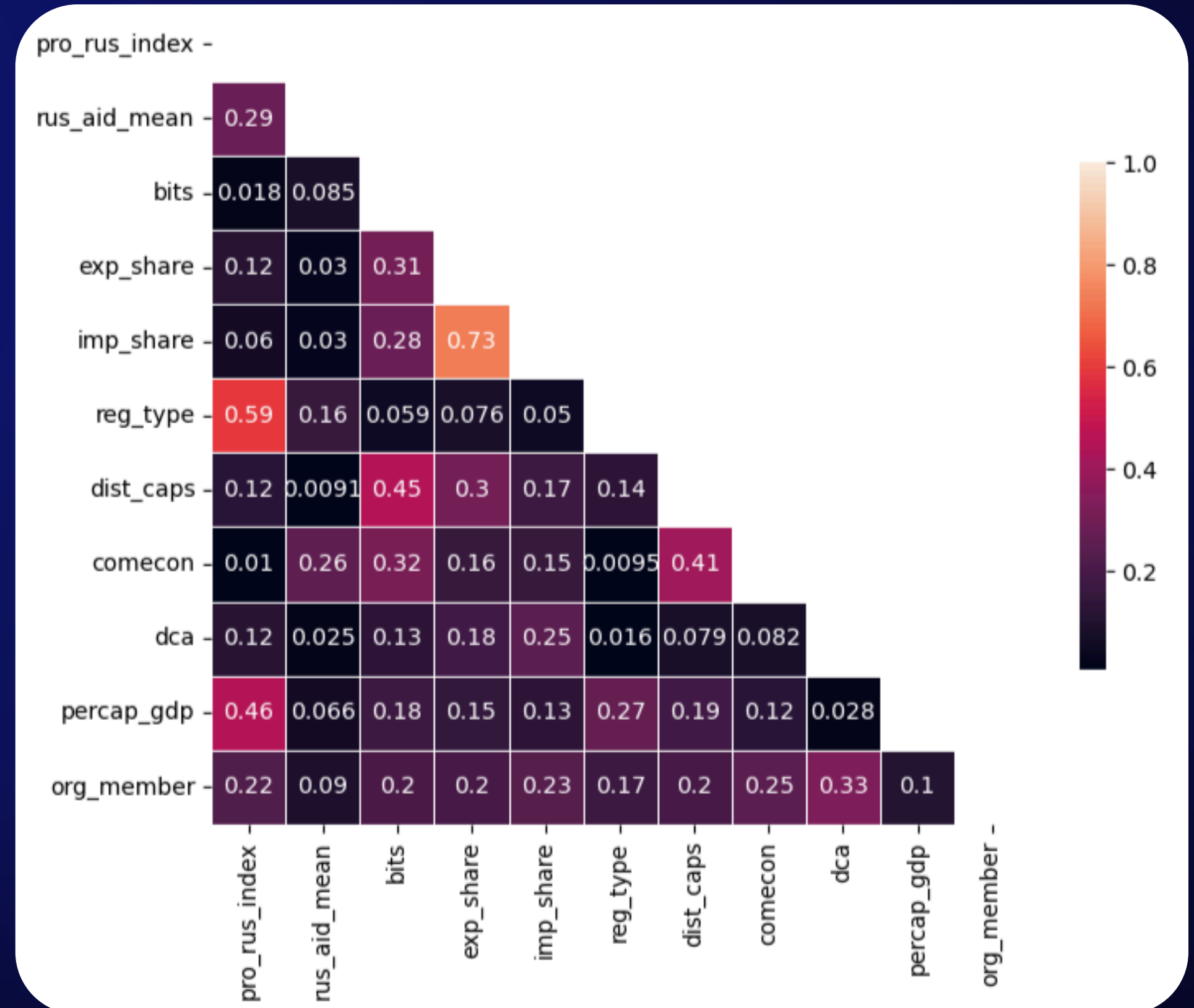
- Bilateral Investment Treaty
- Comecon Membership
- Import Partner Share

## High Feature Correlation

- Import and Export Partner Share
- Already dropped Import

## Feature Engineering

- Normalization of features for distance-based ML models due to big difference in values (GDP per capita, distance to Moscow etc.)





# OVERVIEW OF MODEL PERFORMANCE

**Distance-Based Models** with normalized features and transformed target

Model	$R^2$	Cross-Validation $R^2$
KNN	0.50	0.42
Linear Regression	0.32	0.28

- Performance drop after cross-validation indicates that the models were not generalising well before due to the quite small dataset with features that vary a lot for every country
- Selected random state 42 performed better than the average of multiple train/test splits

# OVERVIEW OF MODEL PERFORMANCE

## Decision Tree and Ensemble Methods

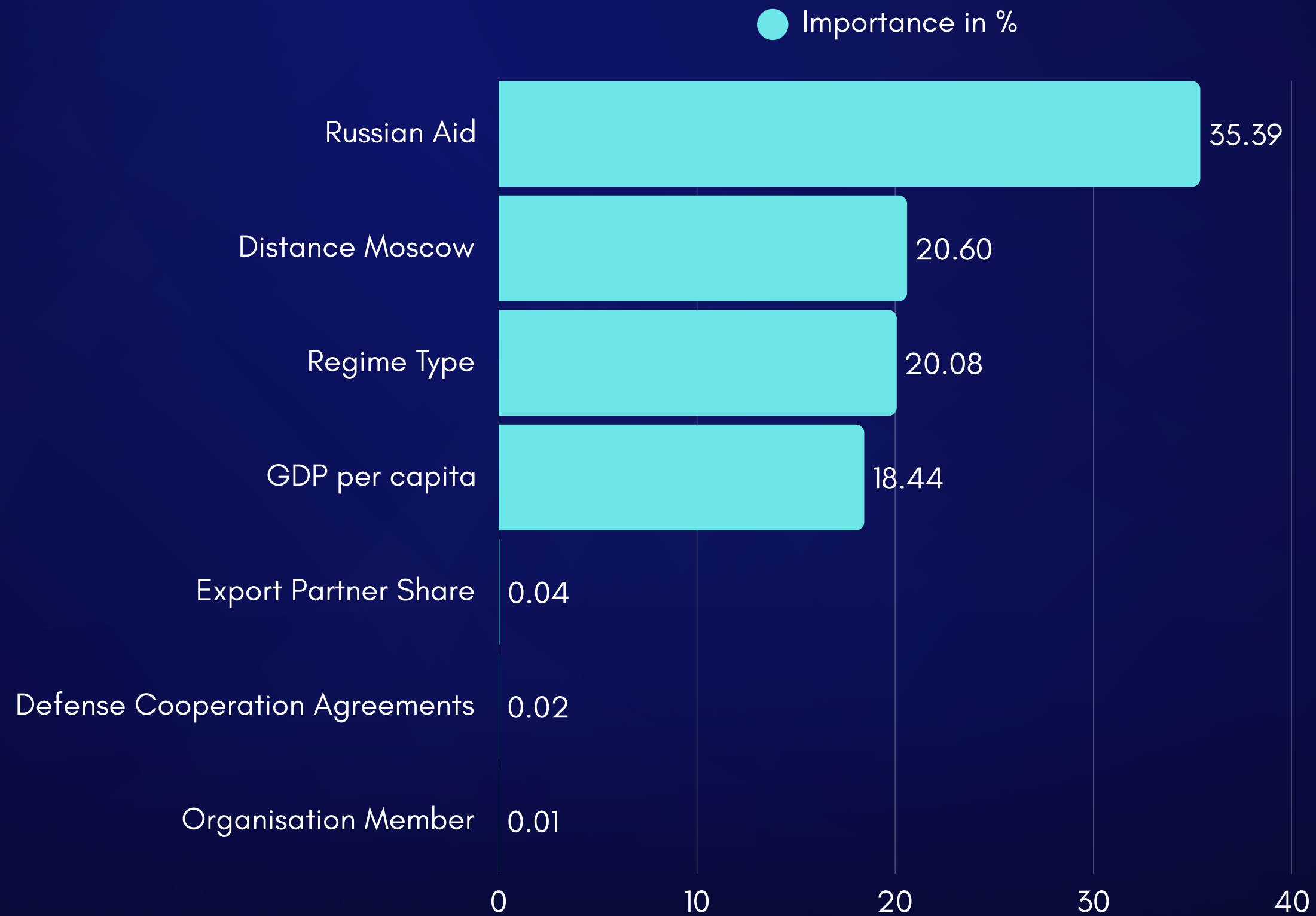
Model	R <sup>2</sup>	Cross-Validation R <sup>2</sup>
Decision Tree	0.65	0.36
Random Forest	0.61	<b>0.56</b>
Ada Boost	0.54	0.53
Gradient Boost	0.46	0.51

Since performance drop legitimate – best model Random Forest with R<sup>2</sup> of 0.56



# KEY FINDINGS

## Feature Importance in Random Forest Model



# LIMITATIONS & FUTURE WORK

## Explaining vs. Predicting

- Focus rather on *explaining features* that lead to outcome than training a model to be able to predict the outcome itself
- Models do not have much application in making actual predictions because no new “rows” expected (new countries joining UN)
- Only if country characteristics change, do the predictions change

## Model Performance

- $R^2$  of 0.56 indicates room for improvement – missing features?
- Future work could include additional features which matter for predicting Pro-Russian voting (requires theoretical research before model building)

## Methods

- Trying more advanced models?
- Using Time-series data?

# CONCLUSION

## Four Important Features in Pro-Russian Voting Identified

- **Russian Aid:** Countries that receive more development assistance from Russia, on average have a higher Pro-Russian Voting Index
- **Distance to Moscow:** Russia on average receives the most voting support from countries that are located further away
- **Regime Type:** Authoritarian countries on average have a higher voting alignment with Russia than democracies
- **GDP per Capita:** Countries with a lower GDP per capita on average tend to support Russia more in the UNGA than countries with a higher GDP per capita

## Evidence for Hypothesis Found

- Import and Export Partner Share & Bilateral Investment Treaties not relevant (economic ties)
- Receipt of Russian Aid most important feature & GDP per capita important (dependencies)
- Economic dependencies on Russia are the strongest predictor for voting alignment with Russia in the UNGA – Russia indeed seems to be buying friends



The background is a dark blue gradient. It features several light blue, wavy, horizontal lines that flow across the top and bottom of the slide. Scattered throughout the background are numerous small, white and light blue stars, some of which are grouped together in clusters, particularly in the top right and bottom left corners.

THANK YOU

BUYING FRIENDS?

MODELLING PRO-RUSSIAN VOTING BEHAVIOUR  
IN THE UNITED NATIONS GENERAL ASSEMBLY

DATA SCIENCE PROJECT BY MARIA