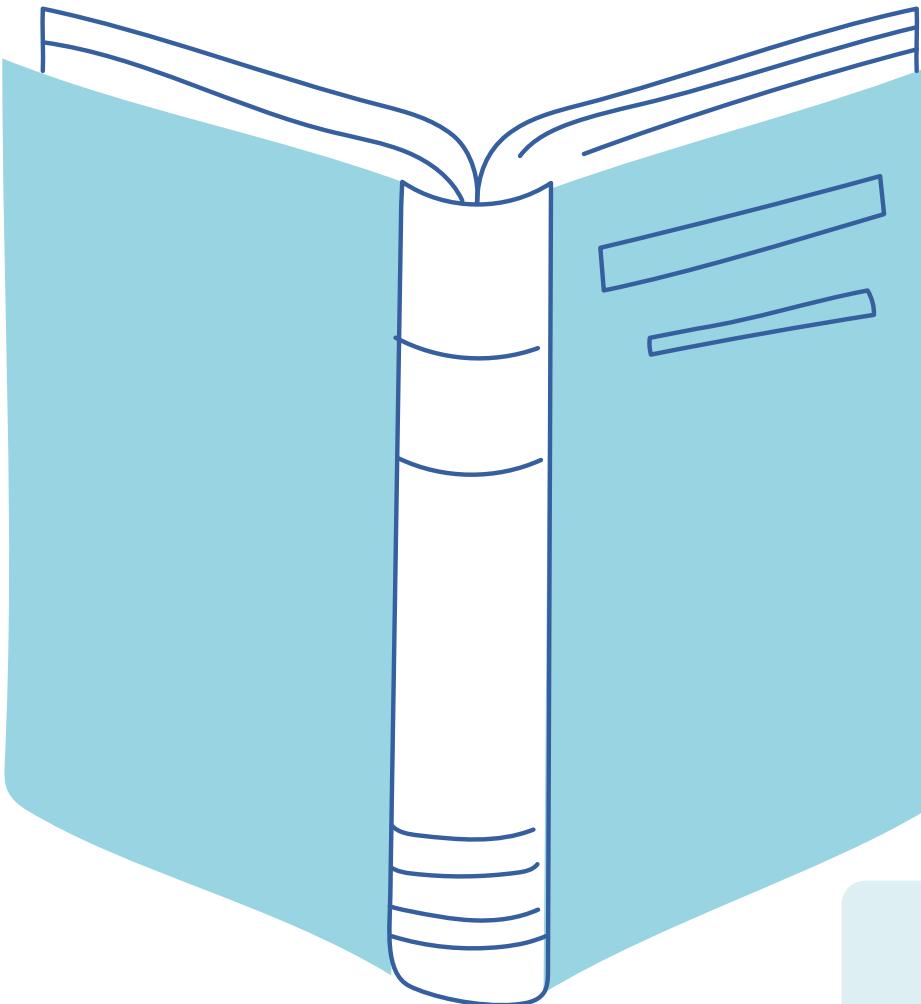




Final Project  
Presentation



# **Academic Reference Quality Scoring System Using Machine Learning**

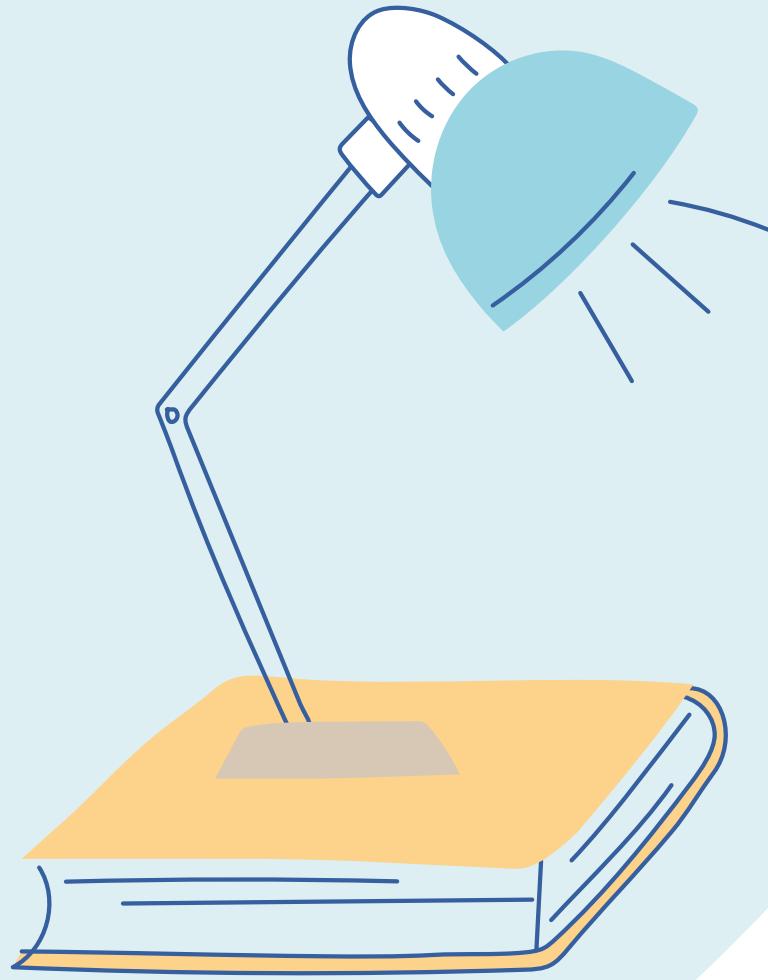
By S.Faizullayev &

M.Kamal Zada

Astana IT University

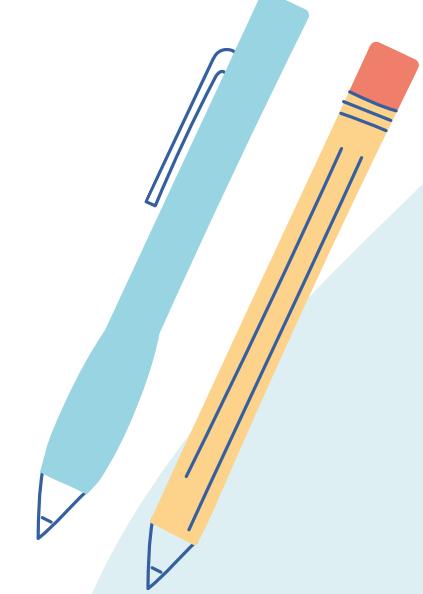
Research Project IP 2218

Instructor: Assiya Karatay



# Overview

- Introduction 03
  - Project Goal 04
  - Data 05
- Methodology
- System Pipeline 06
  - Model Architecture 07
  - Training Setup 08
  - Experiments & Results 09
  - Discussion & Limitations and Future Work 10
  - Conclusions 11
  - References 12



# **Introduction**

We propose an automated system that assigns quality scores to academic references using machine learning.

## **Problem & Motivation**

### **Why This Project Matters**

- Academic papers rely on references to support claims
- Many references are outdated, weak, or from low-quality sources
- Manual checking of references is slow and subjective
- Need for an automatic system to score reference quality



# Project objectives

01

*Build a system  
that predicts the  
quality score of  
academic  
references*

02

*Use reference  
metadata (year,  
citations,  
publisher,  
authors, etc.)*

03

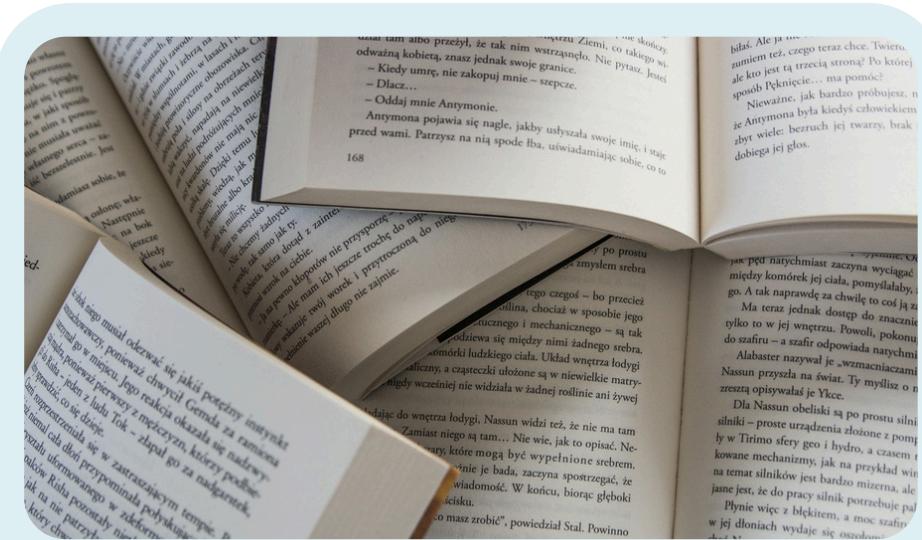
*Compare  
machine  
learning models*

04

*Provide a usable  
tool for students  
and researchers*

# Dataset & Data

Sources: CrossRef, Google Scholar, Semantic Scholar



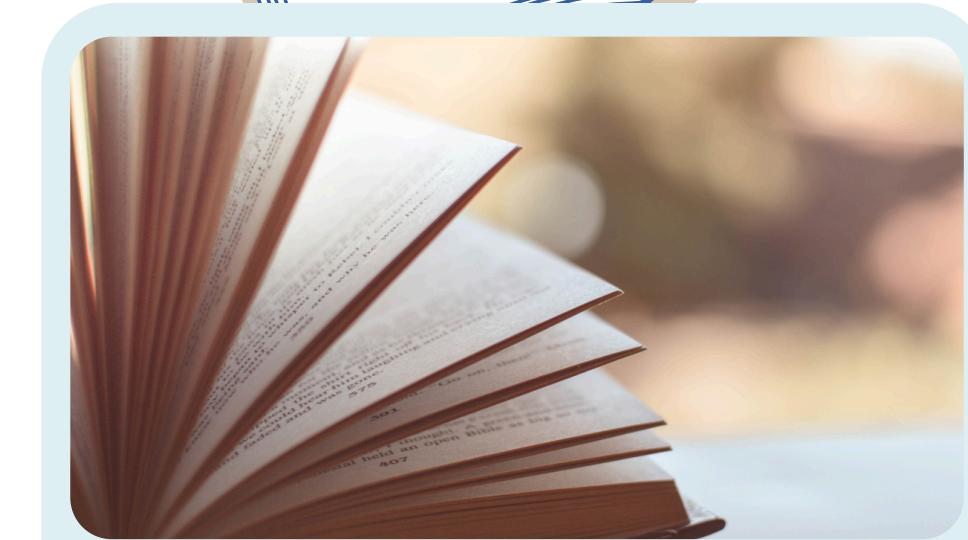
## Features

- Publication year
- Citation count
- Publisher / journal
- Number of authors
- Document type



## Labels

Continuous quality score based  
on predefined rules



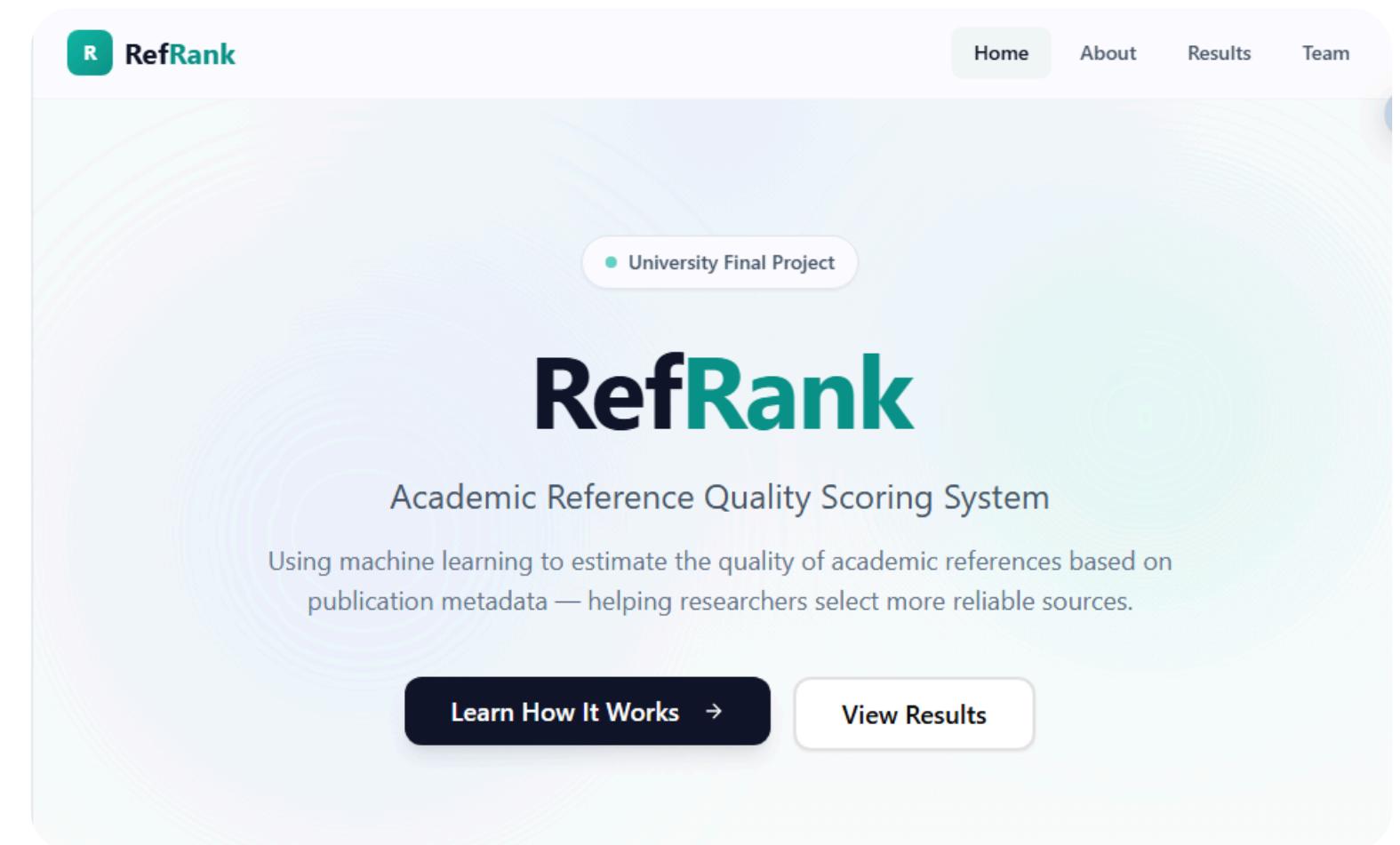
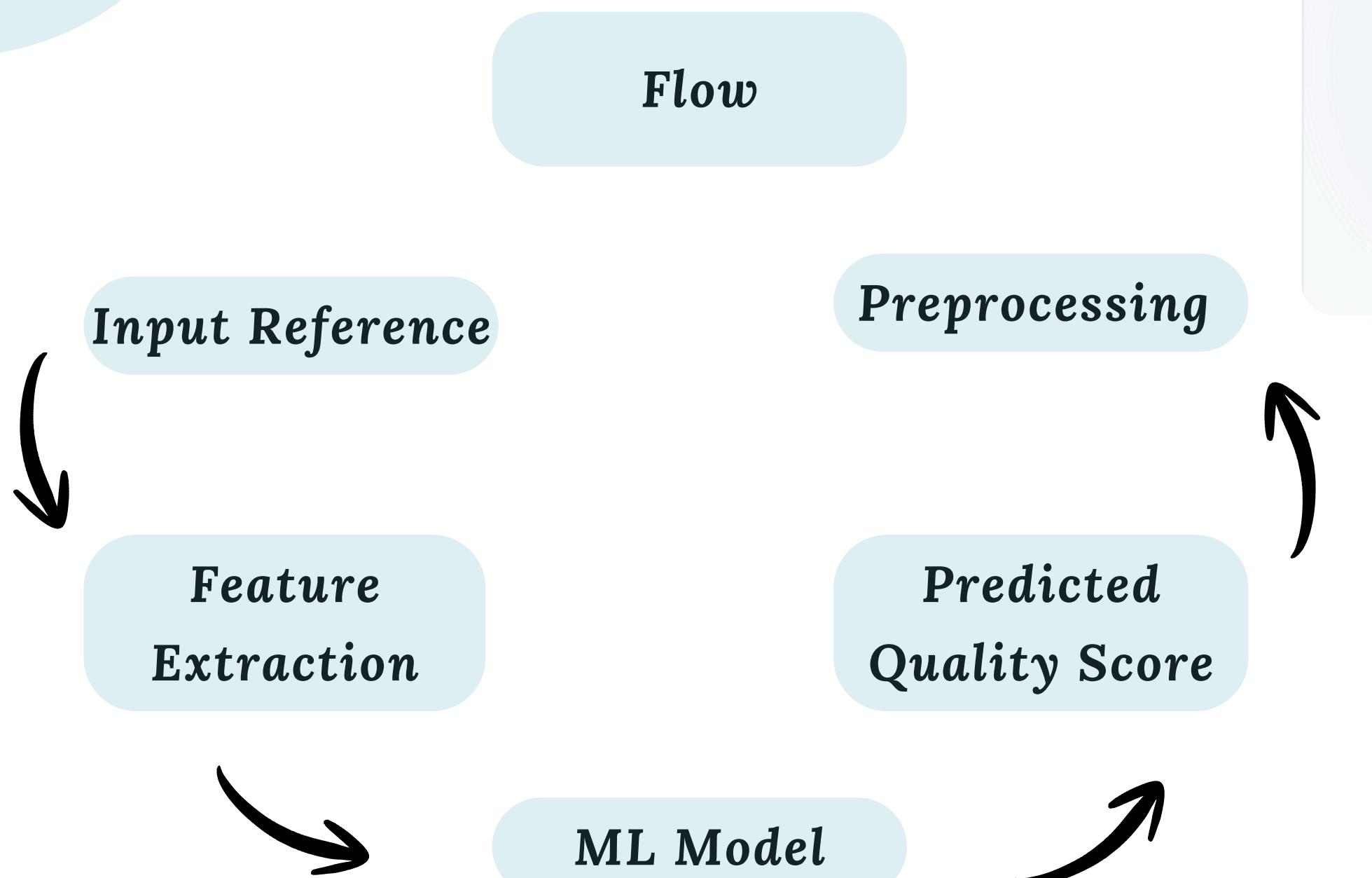
## Split

- 80% training
- 20% testing



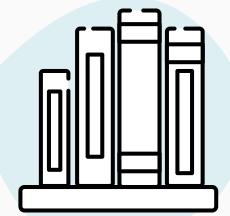
Methodology

# System Architecture



## Methodology

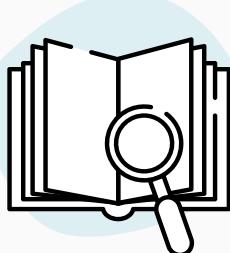
# Machine Learning Model



**Neural network regression model**



**Regularization: Dropout + L2**



**Input: reference metadata**



**Activation: GELU**



**Hidden layers:**

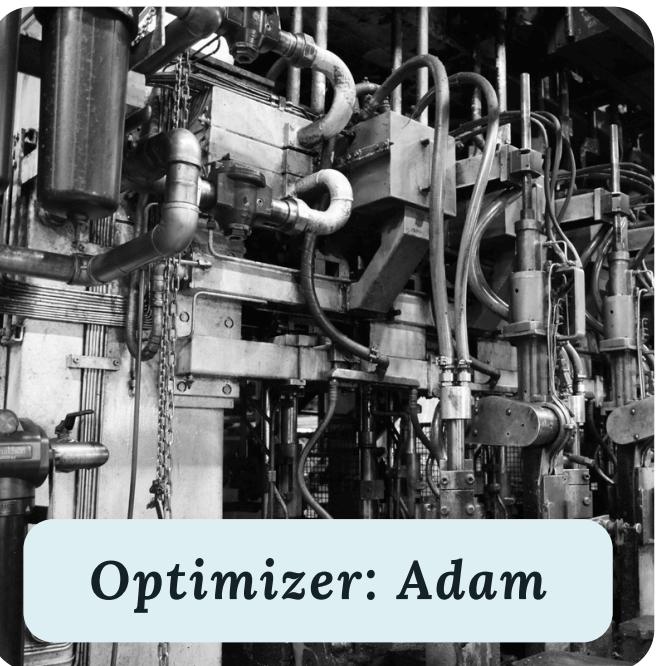
- 128 neurons
- 64 neurons



**Output: continuous quality score**



## Training Procedure



**Optimizer:** Adam



**Loss:** Mean Squared  
Error



**Metrics:**

- RMSE
- MAE



**Hyperparameters:**

- Learning rate search
- Batch size tuning



# Experiments

01

1: Learning rate tuning

2: Model comparison

- Baseline
- Linear regression
- Random Forest
- Neural Network



Back to Preview

pages/Results

Read-only view

Checkpoint Files

- Reference
- Revenue
- SustainabilityGoal
- TeamMember

pages

- About
- Announcements
- Composting
- Customers
- Dashboard
- EnergyMonitoring
- Expenses
- Home
- MyImpact
- ResidentEngagement
- Results
- Revenue
- Team

```
1 import React, { useState, useEffect } from "react";
2 import { base44 } from "@/api/base44Client";
3 import { Card,CardContent,CardHeader,CardTitle } from "@/components/ui/card";
4 import { Badge } from "@/components/ui/badge";
5 import { Table,TableBody,TableCell,TableHeader,TableRow } from "@/components/ui/table";
6 import { BarChart,Bar,XAxis,YAxis,CartesianGrid,Tooltip,ResponsiveContainer,PieChart,Pie,
Cell } from 'recharts';
7 import { TrendingUp,Award,Database,Target } from "lucide-react";
8
9 const COLORS = ['#10b981', '#3b82f6', '#f59e0b'];
10
11 export default function Results() {
12   const [references, setReferences] = useState([]);
13   const [isLoading, setIsLoading] = useState(true);
14
15   useEffect(() => {
16     loadData();
17   }, []);
18
19   const loadData = async () => {
20     setIsLoading(true);
21     try {
22       const refs = await base44.entities.Reference.list('-quality_score');
23       setReferences(refs);
24     } catch (error) {
25       console.error('Error loading data:', error);
26     }
27     setIsLoading(false);
28   };
29
30   const avgScore = references.length > 0
31   const avgScoreLabel = references.length > 0
32 }
```

# Results

02

- Neural network achieved lowest RMSE and MAE
- Better performance on difficult cases
- Stable predictions across score range
- $R^2 > 0.85$

# Discussion



- **Model can separate high-quality and low-quality references**
- **Metadata alone works reasonably well**



## Useful for:

- Academic writing tools
- Reference managers
- Peer review support



## Points:

- Labels are based on rules, may include bias
- No full-text analysis yet
- Dataset may not cover all research fields



## Future:

- Add abstract and text analysis
- Use NLP for context relevance
- Expand dataset

# Limitations & Future Work

# Conclusions

01



*Built an automated  
reference quality  
scoring system*

02



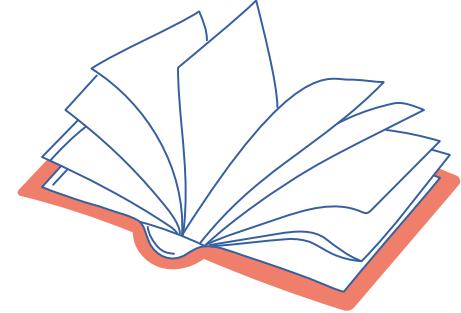
*Machine learning  
improves reliability  
of reference selection*

03



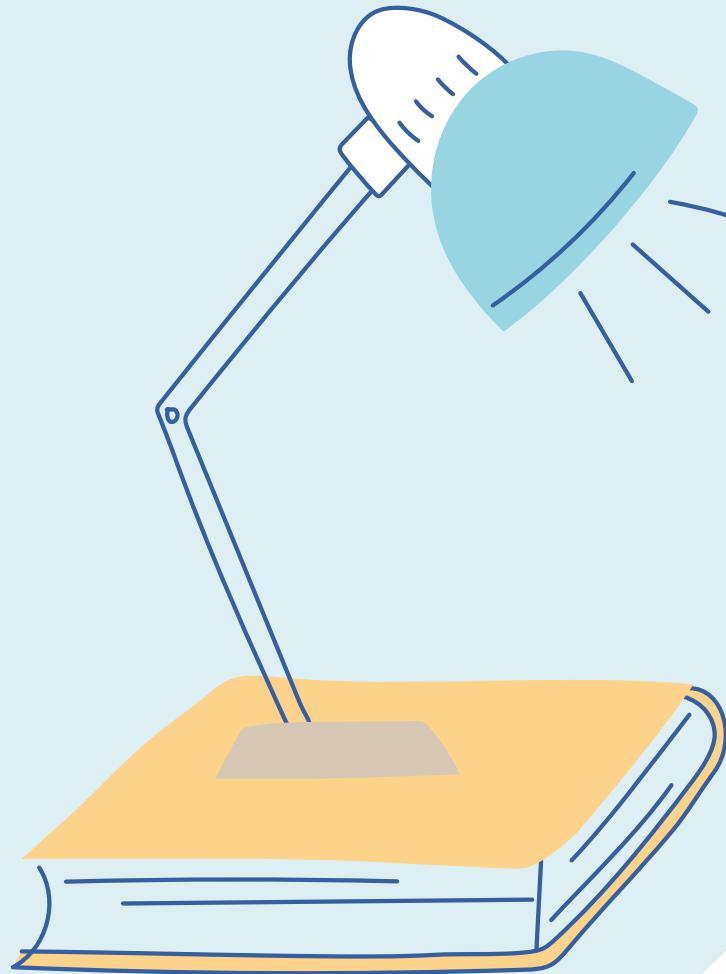
*Can help researchers  
choose better sources*

04



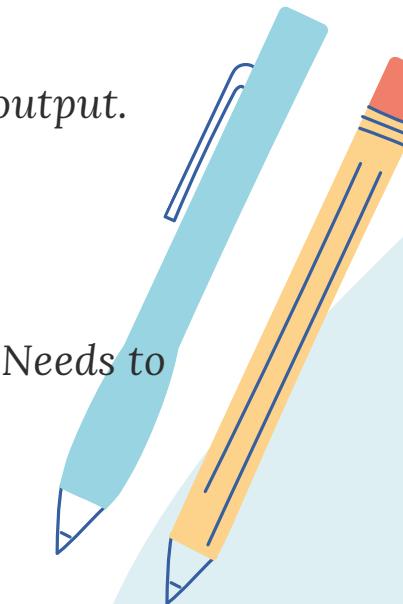
*Ready to be  
integrated into tools  
and platforms*

[App Link:](#)



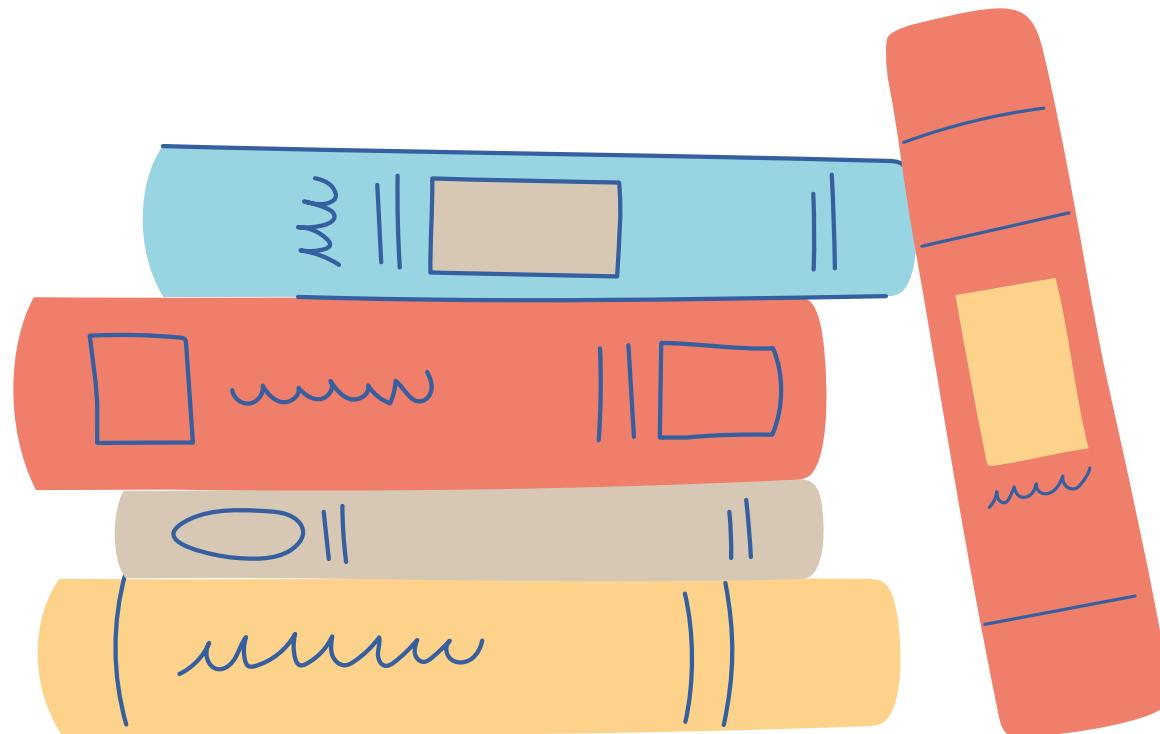
# Reference

- 1. Garfield, E. (1972). Citation analysis as a tool in journal evaluation. *Science*, 178(4060), 471–479. <https://doi.org/10.1126/science.178.4060.471>
- 2. Bornmann, L., & Daniel, H. D. (2008). What do citation counts measure? A review of studies on citing behavior. *Journal of Documentation*, 64(1), 45–80.  
<https://doi.org/10.1108/00220410810844150>
- 3. Moed, H. F. (2005). *Citation Analysis in Research Evaluation*. Springer.  
<https://doi.org/10.1007/1-4020-3714-7>
- 4. Waltman, L. (2016). A review of the literature on citation impact indicators. *Journal of Informetrics*, 10(2), 365–391. <https://doi.org/10.1016/j.joi.2016.02.007>
- 5. Hirsch, J. E. (2005). An index to quantify an individual's scientific research output. *Proceedings of the National Academy of Sciences*, 102(46), 16569–16572.  
<https://doi.org/10.1073/pnas.0507655102>
- 6. Sugimoto, C. R., & Larivière, V. (2018). *Measuring Research: What Everyone Needs to Know*. Oxford University Press





The End



**Thank you  
Question !**



# Research Project: Academic Reference Quality Scoring System

## Overview

This project implements a machine learning pipeline for evaluating the quality of academic references using bibliographic metadata.

The system leverages real publication data obtained from the **Semantic Scholar Academic Graph API** and predicts a continuous **reference quality score**.

The project focuses on:

- metadata-based feature extraction
  - supervised regression modeling
  - quantitative evaluation using standard ML metrics
- 

## How to Run This Notebook

### 1. Environment

This notebook is designed to run in **Google Colab**.

No manual dataset upload is required — data is fetched automatically from a public API.

---

### 2. Install & Import Dependencies

All required libraries are standard in Google Colab:

- pandas
- numpy
- scikit-learn
- requests
- (optional) tensorflow / keras for neural network experiments

No additional installation steps are needed.

---

### 3. Data Collection

The dataset is obtained programmatically from the **Semantic Scholar Academic Graph API** using a keyword-based search (e.g., "*machine learning*").

Extracted metadata includes:

- publication year
- citation count
- number of authors
- venue availability

These attributes are commonly used in scientometric analysis.

---

## 4. Feature Engineering & Label Construction

A continuous **quality score (0–1)** is constructed using transparent, rule-based weighting of metadata features:

- citation impact
- publication recency
- authorship
- venue presence

This enables regression-based learning and comparison across models.

---

## 5. Model Training

The notebook supports multiple models:

- **Random Forest Regressor** (baseline, no epochs required)
- **Neural Network Regressor** (optional, trained with epochs)

Data is split into training and testing subsets (80/20) and standardized prior to training.

---

## 6. Evaluation Metrics

Model performance is evaluated using:

- **RMSE** (Root Mean Squared Error)
- **MAE** (Mean Absolute Error)
- **R<sup>2</sup> Score**

Additionally, an optional categorical accuracy is computed by mapping scores to:

- High / Medium / Low quality classes

## 7. Output

The processed dataset is saved locally as: semantic\_scholar\_dataset.csv This allows reproducibility and reuse in further experiments.

## Notes

- The system validates the **methodology and ML pipeline**, not absolute scholarly quality.
- Full-text and NLP-based analysis are considered future work.
- The approach is suitable for early-stage research and academic tooling prototypes.

## Authors:

Mustafa Kamal Zada, Salim Faizullayev

IP2218 Research Project

Instructor: Assiya Karatay

Academic Reference Quality Scoring System

Astana IT University

```
import time
import numpy as np
import pandas as pd
import requests

from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import mean_squared_error, mean_absolute_error
from sklearn.ensemble import RandomForestRegressor

np.random.seed(42)
```

```
BASE_URL = "https://api.semanticscholar.org/graph/v1/paper/search"

def fetch_papers(query: str, total: int = 800, batch: int = 100, sleep_s: float = 0):
    out = []
    offset = 0

    fields = "title,year,citationCount,authors,venue"

    while len(out) < total:
        limit = min(batch, total - len(out))
        params = {
            "query": query,
            "limit": limit,
            "offset": offset,
            "fields": fields
        }
        r = requests.get(BASE_URL, params=params, timeout=60)

        if r.status_code == 429:
            # rate limit; wait and retry
            time.sleep(max(3.0, sleep_s) * 2)
            continue

        r.raise_for_status()
        data = r.json()

        batch_data = data.get("data", [])
        if not batch_data:
            break

        out.extend(batch_data)
        offset += limit
        time.sleep(sleep_s)

    return out

papers = fetch_papers(query="machine learning", total=800, batch=100)
print("Fetched papers:", len(papers))
print(papers[0].keys())

Fetched papers: 800
dict_keys(['paperId', 'title', 'venue', 'year', 'citationCount', 'authors'])
```

```
def safe_num_authors(authors):
    if not authors:
        return 1
    return max(1, len(authors))

rows = []
for p in papers:
    rows.append({
        "year": p.get("year"),
        "citationCount": p.get("citationCount", 0),
        "num_authors": safe_num_authors(p.get("authors")),
        "venue": p.get("venue")
    })

df = pd.DataFrame(rows)

df["citationCount"] = pd.to_numeric(df["citationCount"], errors="coerce")
df = df.dropna(subset=["year"])
df = df[(df["year"] >= 1900) & (df["year"] <= 2030)]
df["has_venue"] = df["venue"].notna().astype(int)

print("Rows after cleaning:", len(df))
df.head()
```

Rows after cleaning: 797

	year	citationCount	num_authors	venue	has_venue
0	2021.0	5377	6	Nature Reviews Physics	1
1	2021.0	3950	1	SN Computer Science	1
2	2017.0	10082	3	arXiv.org	1
3	2019.0	5323	5	ACM Computing Surveys	1

## Proxy Reference Quality Score

The reference quality score is defined using a rule-based composite formulation inspired by established bibliometric evaluation frameworks, including the Article Influence Score and Reference Quality Scoring Systems (RQSS) used in scholarly databases and knowledge graphs to assess credibility and trustworthiness of references [1], [2]. These approaches evaluate reference quality by combining multiple normalized indicators rather than relying on raw citation counts alone. In line with these principles, the proposed score integrates available reference metadata, including citation count as a measure of scholarly influence, publication year to capture recency effects, number of authors as an indicator of collaborative strength, and venue availability as a basic credibility signal. The resulting composite score provides a continuous target variable suitable for supervised learning experiments in automated reference quality assessment.

## References

[1] C. T. Bergstrom, J. D. West, and M. A. Wiseman, "The Eigenfactor™ metrics," Journal of Neuroscience, vol. 28, no. 45, pp. 11433–11434, 2008.

<https://doi.org/10.1523/JNEUROSCI.0003-08.2008>

[2] C. R. Sugimoto and V. Larivière, Measuring Research: What Everyone Needs to Know. Oxford, UK: Oxford University Press, 2018, pp. 1–152.

[https://www.researchgate.net/publication/346866471\\_Measuring\\_Research\\_What\\_Everyone\\_Needs\\_to\\_KnowRWhat\\_Everyone\\_Needs\\_to\\_KnowR](https://www.researchgate.net/publication/346866471_Measuring_Research_What_Everyone_Needs_to_KnowRWhat_Everyone_Needs_to_KnowR)

```
year_norm = (df["year"] - df["year"].min()) / (df["year"].max() - df["year"].min())
cit_norm = np.log1p(df["citationCount"]) / (np.log1p(df["citationCount"]).max() - np.log1p(df["citationCount"]).min())
auth_norm = (df["num_authors"] - 1) / (df["num_authors"].max() - 1 + df["num_authors"].min())

df["quality_score"] = (
    0.45 * cit_norm +
    0.35 * year_norm +
    0.15 * auth_norm +
    0.05 * df["has_venue"] +
    np.random.normal(0, 0.03, size=len(df))
).clip(0, 1)

df[["year", "citationCount", "num_authors", "has_venue", "quality_score"]]
```

	year	citationCount	num_authors	has_venue	quality_score
0	2021.0	5377	6	1	0.744217
1	2021.0	3950	1	1	0.707090
2	2017.0	10082	3	1	0.747557
3	2019.0	5323	5	1	0.762145
4	2018.0	7706	1	1	0.713754

```
X = df[["year", "citationCount", "num_authors", "has_venue"]]
y = df["quality_score"]

X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=0.2, random_state=42
)

scaler = StandardScaler()
X_train_s = scaler.fit_transform(X_train)
X_test_s = scaler.transform(X_test)
```

```
model = RandomForestRegressor(  
    n_estimators=300,  
    random_state=42,  
    n_jobs=-1  
)  
model.fit(X_train_s, y_train)
```

```
▼ RandomForestRegressor  
RandomForestRegressor(n_estimators=300, n_jobs=-1, random_state=42)
```

```
y_pred = model.predict(X_test_s)  
  
rmse = np.sqrt(mean_squared_error(y_test, y_pred))  
mae = mean_absolute_error(y_test, y_pred)  
r2 = r2_score(y_test, y_pred)  
  
print("Research Project – Model Evaluation")  
print(f"RMSE: {rmse:.4f}")  
print(f"MAE: {mae:.4f}")  
print(f"R2: {r2:.4f}")
```

```
Research Project – Model Evaluation  
RMSE: 0.0326  
MAE: 0.0262  
R2: 0.7568
```

```
def to_bin(v):  
    if v >= 0.75:  
        return "High"  
    if v >= 0.40:  
        return "Medium"  
    return "Low"  
  
true_bin = y_test.apply(to_bin).values  
pred_bin = pd.Series(y_pred).apply(to_bin).values  
  
acc = (true_bin == pred_bin).mean()  
print(f"Binned Accuracy: {acc:.2%}")
```

```
Binned Accuracy: 98.75%
```

```
df.to_csv("semantic_scholar_dataset.csv", index=False)
print("Saved: semantic_scholar_dataset.csv")
```

```
Saved: semantic_scholar_dataset.csv
```