DA 231o: Data Engineering at Scale
Course Project

Real Time Fake News Prediction

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Introduction: How we Started

In today's digital age, we're drowning in information. But how much of it is true?

- Social media spreads news at lightning speed.
- Misinformation spreads faster than truth.
- People can’t deal with 1000s of articles being generated every day.
- Can machines help us detect fake news automatically?

Build a system to automatically provide a probability for a news story to be fake or real using distributed machine learning, with a target confidence score of 80%. Decrease the number of humans required by over 10 times to make the pipeline accurate and scalable enough to handle the massive data being generated.

Journey Begins : Understanding the Data

Let's start by understanding what makes fake news different from real news.

What We Did,

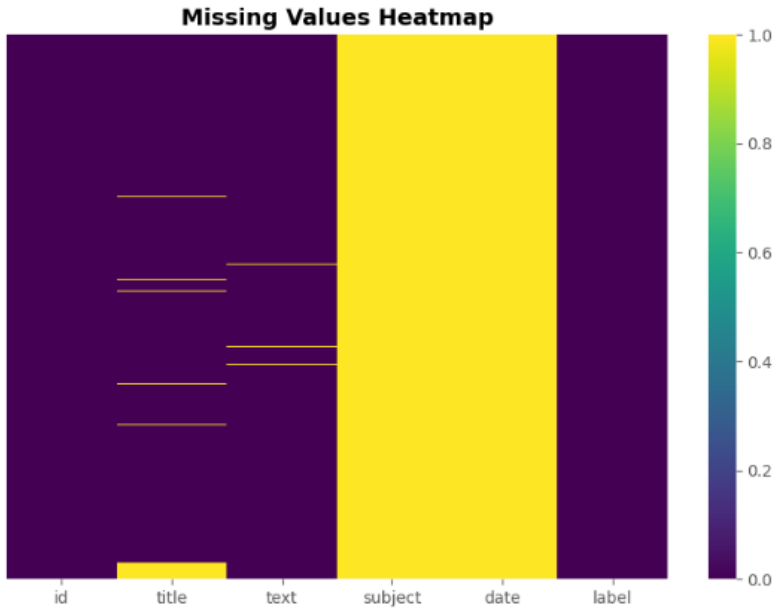
- Loaded a dataset of thousands of news articles (both fake and real).
- Each article had a title, text content, and a label (Fake, Real).

First Impressions,

- Dataset contained a mix of political, social, and general news.
- Articles varied greatly in length and writing style.
- We had both titles and full article text to work with.

Detective Work : EDA Begins

We Started With Data Quality Check,



Missing Value Analysis,

- Checked every column for missing or incomplete data.
- Found some articles had missing titles or text.

Class Distribution,

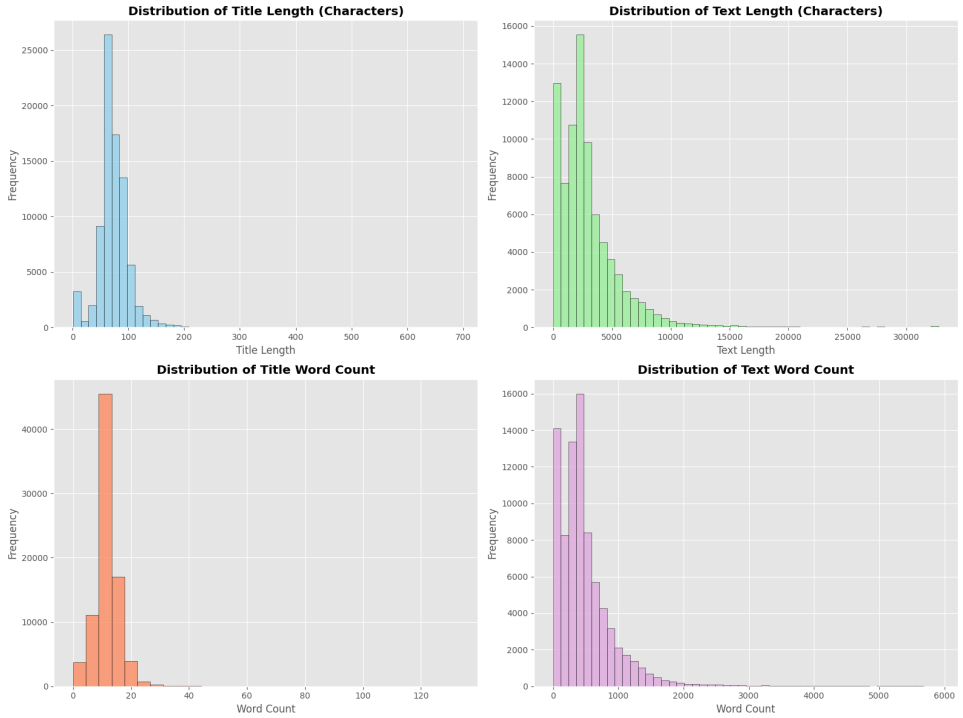
- Counted how many fake vs real articles we had.
- Checked if dataset was balanced or biased.

What We Found,

Some data cleaning would be needed, and Data has enough balance to train reliable models.

The First Clue : Text Patterns

Do fake news articles write differently?
Are they longer or shorter?



Measured Everything,

- Title length (characters and words).
- Article length (characters and words).

Visualization showed,

- Real news: More consistent length, professional structure.
- Fake news: More variable, sometimes unusually short or long.
- Titles: Fake news titles often more sensational (longer/shorter extremes).

What We Found,

Fake news doesn't follow the same writing patterns as professional journalism!

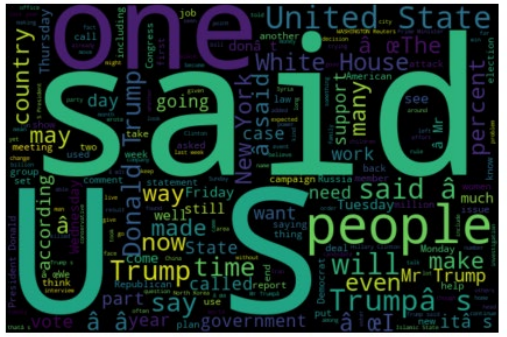
The Language Clue : Word Clouds and Frequency

What words do fake news use? Are there signature phrases?

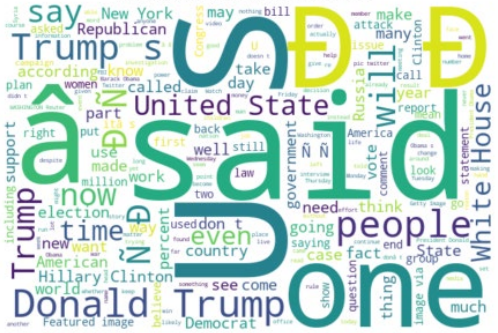
Create word clouds,

- Separate clouds for fake vs real news.
- Removed common stop words.
- Highlighted most frequent terms.

Fake News Word Cloud



Real News Word Cloud



Visualization showed,

- Real news: Professional tone, Specific names, places, dates, Balanced language.
- Fake news: More capital letters, words like “Breaking”, “Shocking”, “Urgent”, Emotional and sensational language.

What We Found,

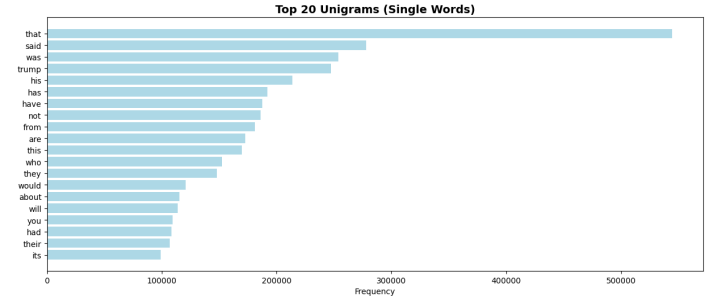
The language itself is a fingerprint!

Going Deeper : N-Gram Patterns

Single words are good, but what about phrases? Combinations might reveal more!

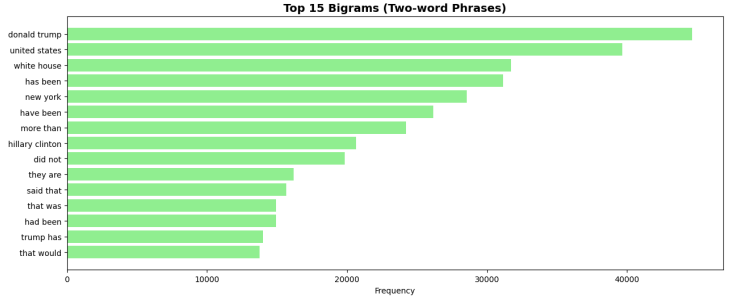
Unigrams (Single words),

- Most common individual words overall



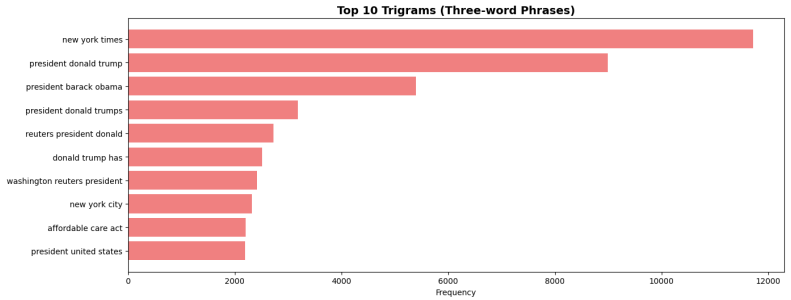
Bigrams (Two-word phrases),

- Real :"according to", "officials said", "data shows"
- Fake : "breaking news", "urgent update", "sources say"



Trigrams (Three-word phrases),

- Real: "according to the", "research shows that"
- Fake: "you won't believe", "this is shocking"



What We Found,

Fake news uses predictable clickbait phrases! Real news cites sources properly!

The Emotion Factor : Sentiment Analysis

Fake news probably plays with emotions. Let's measure sentiment!

Analyzed,

- Sentiment Score: Positive, Negative, or Neutral.
- Subjectivity: Objective facts vs subjective opinions.
- Compared fake vs real news distributions.

Sentiment Patters,

- Fake news: Extreme sentiments, Higher subjectivity scores.
- Real news: More neutral, balanced sentiment.

What We Found,

Fake news triggers emotions! Real news reports facts!

EDA Completes : What we learned?

Journalism has standards. Does writing complexity differ?

Fake News Signature Traits,

- Sensational vocabulary, Extreme sentiments and Clickbait phrases.
- More punctuation (!!!, ???) and Higher subjectivity

Real News Characteristics,

- Professional, neutral tone
- Cites sources properly and Consistent structure
- Balanced sentiment and Factual, objective language

We have clear patterns! Now let's build features and train models!

Building Intelligence : Feature Engineering?

Models need numbers, not words. Let's translate our discoveries into features!

Text Statistics (15+ features),

- Title length, text length, word counts, character counts, Title-to-text ratios

Emotional Indicators and Language Markers,

- Sentiment scores, Subjectivity measures
- Exclamation mark count (!!!), Question mark count (???), CAPS ratio (SHOUTING?), Digit counts, Special character density.

Advanced NLP,

- TF-IDF vectors (word importance), N-gram features

"We've armed our models with 15+ powerful features!"

Getting Ready : Data Preprocessing

Clean data = Better models.

Step 1 : Text Cleaning,

- Combined title + text into one field, Lowercased everything and Removed extra spaces and Fixed encoding issues.
- Removed URLs (http://, www.) and special characters (@#$%^&*).

Step 2 : Label Validation,

- Ensured only 0 (fake) and 1 (real) labels, Removed any invalid entries and Verified data integrity.

Step 3 : Train – Test Split,

- 80% for training (teaching the model), 20% for testing (evaluating performance) and Stratified split (balanced classes)

Getting Ready : Data Preprocessing

Step 4 : Tokenization (for deep learning)

- Vocabulary: Top 10,000 most common words.
- Sequence length: 256 tokens max.
- Added padding for uniform input.

The heavy lifting of data preprocessing is done. But can we run this efficiently? Let's dive into the benchmarks to uncover the scalability limits and define the 'sweet spot' for our Spark pipeline.

Building a Reliable Benchmark Environment

Creating an automated testbed for repeatable and accurate performance results.

The Lab: Single Bare-Metal Server

- **CPU:** Single Bare-Metal, Dual-Socket **Xeon**.
- **RAM:** DDR5, 6400 MT/s
- No network or virtualisation overhead

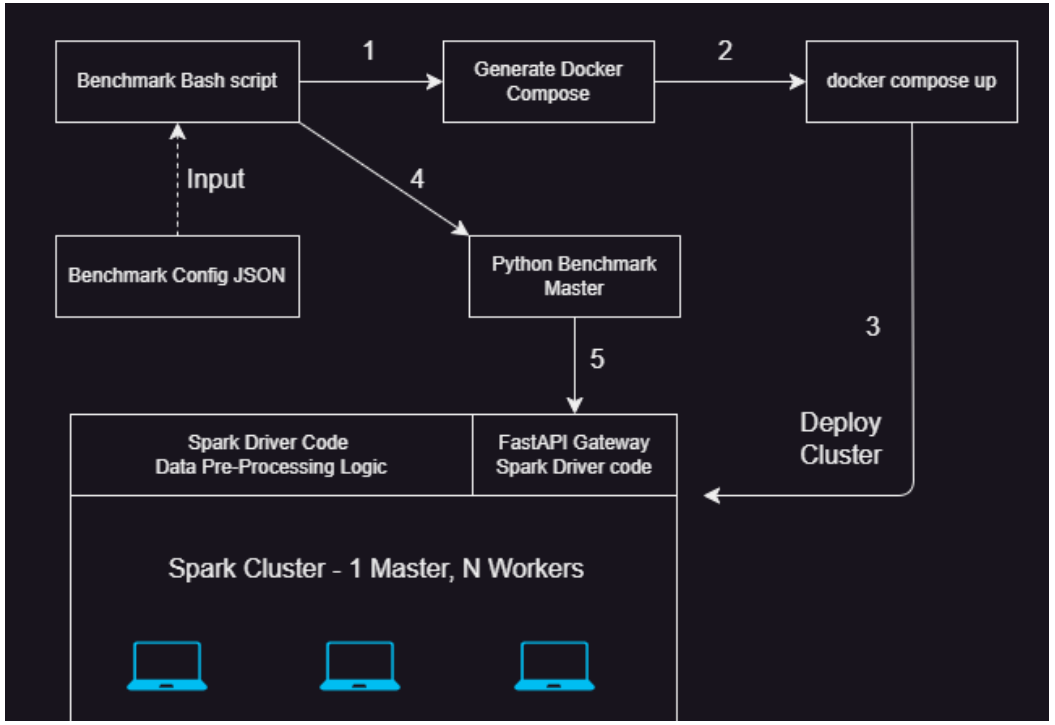
Automation & Libraries

- **Workflow:** Automated via Python/Bash scripts
- **Performance Constraint:** Minimize inter-socket communication through **strict NUMA-pinning**.
- **Tooling: Apache Spark** for data processing; **Sparkmeasure** for metric collection.

```
{
  "name": "SS-4",
  "num_workers": 1,
  "mem_per_worker": 384,
  "cores_per_worker": 4,
  "dataset_scale": 1,
  "log_dir": "./logs/6767P/4
  "remark": "Strong scaling
},
```

NUMA Benchmark

Node	0	1	2	3
0	190.7	189.6	89.0	90.0
1	189.8	189.9	90.1	88.9
2	93.4	94.1	190.3	189.8
3	90.2	89.0	190.1	190.2



Analysis 1: Strong Scaling (Amdahl's Law)

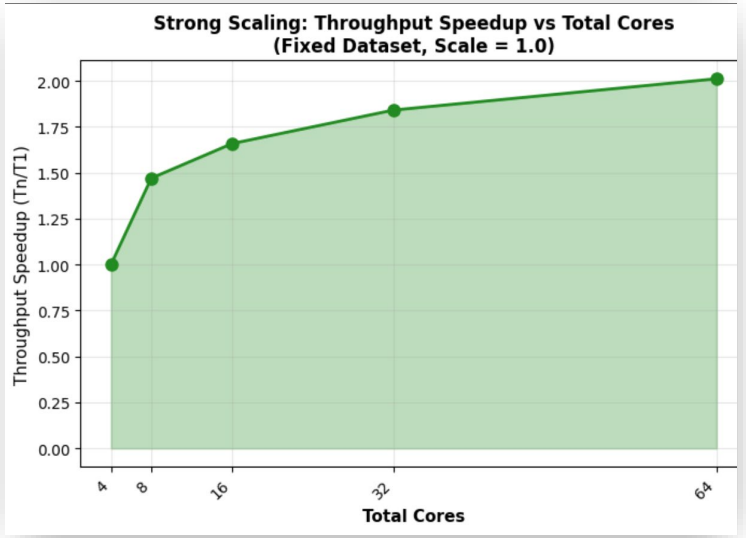
Diminishing returns with more resources for the same problem size.

Num Workers	Cores per Worker	E2E Time	E2E Throughput	Throughput Speedup
1	4	270.34	2933.36	1.00
2	4	183.86	4313.01	1.47
4	4	163.00	4865.14	1.66
8	4	146.84	5400.47	1.84
16	4	134.40	5900.44	2.01

Peak Efficiency: Optimal performance achieved at **4 workers,** yielding a **1.66x peak speedup**.

Bottleneck (The Limit): Scalability flattens dramatically at **32 cores (8 workers)**. The overheads across multiple workers surpass the computational gains.

Conclusion: This is a classic demonstration of **Amdahl's Law**. Sequential component limits speedup; parallelism decreases at a higher number of workers.



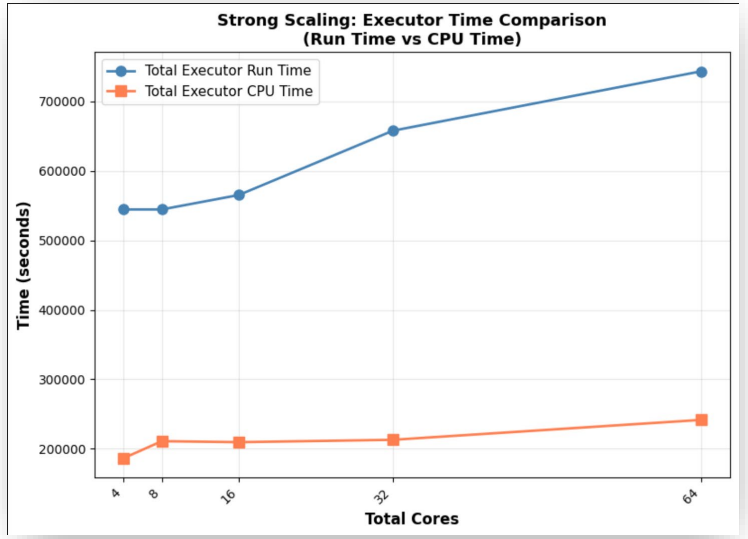
Analysis 1 Deep Dive: Where Did the Time Go?

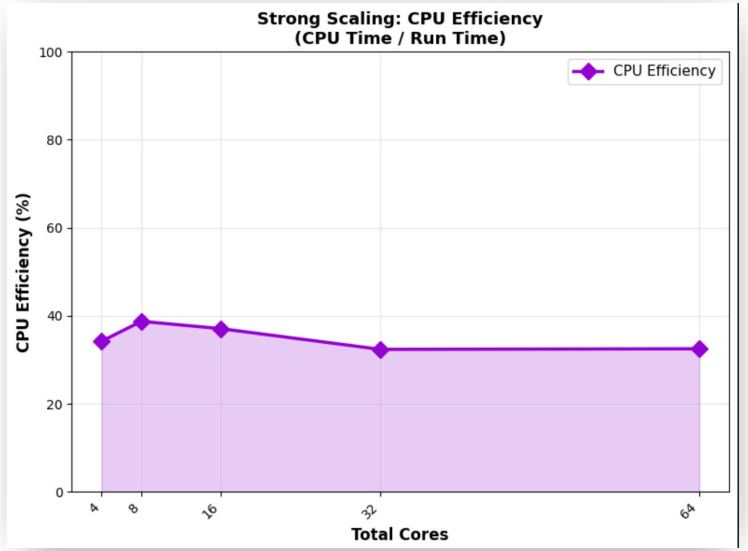
Proving that overhead became the bottleneck.

Metrics: We tracked Executor **Run Time** (total time) vs. **Executor CPU Time** (usable work) to calculate **CPU Efficiency**.

Result: At high scale (64 cores), **Run Time *increased by 36%*** (Anti-Scaling Effect).

Bottleneck: CPU Efficiency remained below 39%. Cores were idle, proving the workload is bottlenecked by **shuffling and I/O overhead**, not computation.





Analysis 2: Weak Scaling (Gustafson's Law)

Increasing efficiency by scaling the resources with problem size

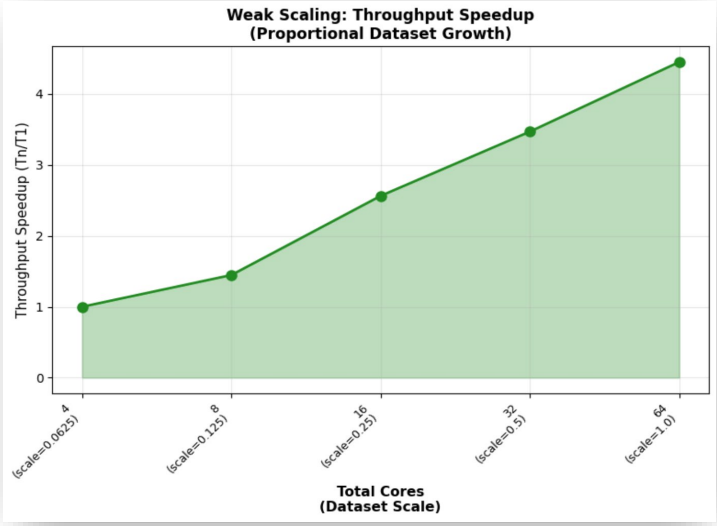
Test: Weak Scaling (Data size proportional to Worker count with 4 cores per worker).

Success: Achieved **4.45x throughput growth** (from 1370.5 to 6098.4 records/sec).

Bottleneck: End-to-End (E2E) Time significantly increased after 16 cores (e.g., 56.45s → 130.04s).

Conclusion: Throughput continues to increase sub-linearly even at 16 workers. Due to overheads, linear scaling could not be achieved.

Num Workers	Dataset scale	E2E Time	E2E Throughput	Throughput Speedup
1	0.0625	36.16	1370.52	1.00
2	0.125	49.99	1983.10	1.45
4	0.25	56.45	3512.11	2.56
8	0.5	83.40	4754.02	3.47
16	1	130.04	6098.38	4.45



Analysis 3: Finding the "Sweet Spot" (Worker Sweep)

Find the best configuration for this 64-core system

The Test: Fixed system (64 cores) and dataset (100%). Varied the **worker-to-core ratio**.

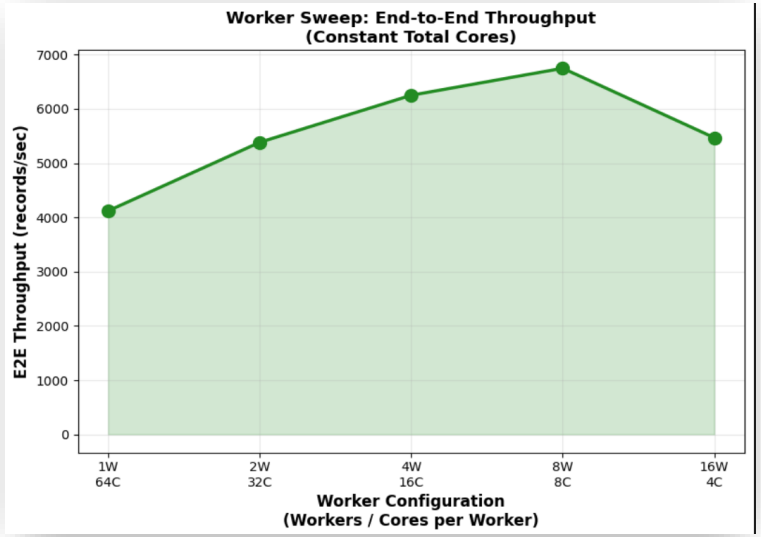
The "Aha!" Moment: The **8 Workers (8 cores/worker)** configuration was the clear winner.

- Achieved the fastest End-to-End (E2E) time (~117s).
- Delivered the highest throughput (>6700 records/sec).

Final Takeaway:

- Too few workers offer poor parallelization.
- Too many workers require excessive scheduling.
- 8W-8C config provided optimal balance.

Num Workers	Cores per worker	E2E Time	E2E Throughput
1	128	268.53	2953.16
2	64	161.92	4897.47
4	32	126.04	6291.50
16	8	132.56	5982.44
32	4	135.90	5835.26



Analysis 3 Deep Dive: Proving the “Sweet Spot”

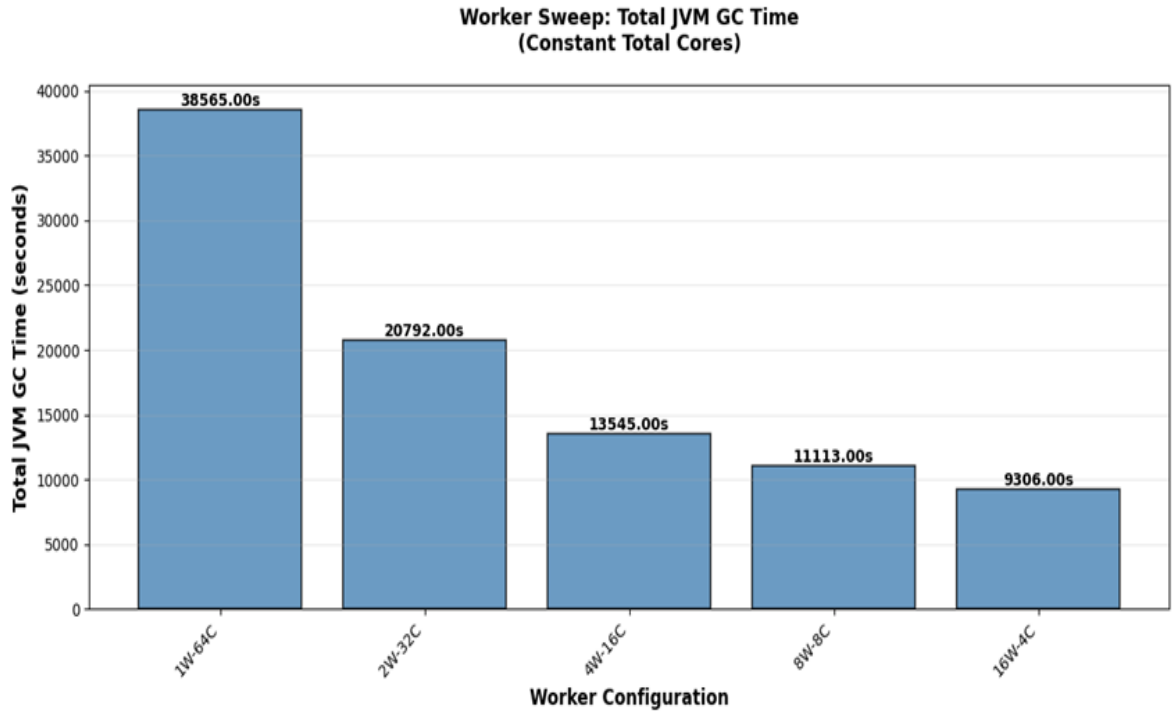
Proving that Garbage Collection and overhead were the primary bottlenecks.

Observation: Garbage Collection (GC) is a **substantial inefficiency** in this Java (Spark) workload.

Case 1 (1W-64C): The single worker's memory was overwhelmed, leading to high GC time.

Case 2 (16W-4C): Achieved the **Lowest Total GC Time,** but worse E2E Time due to **shuffle overhead** from managing 16 executors (JVMs).

Conclusion: The **8 Workers** setup provides the **best balance**, accepting slightly higher GC time to drastically reduce the dominant shuffle overhead.



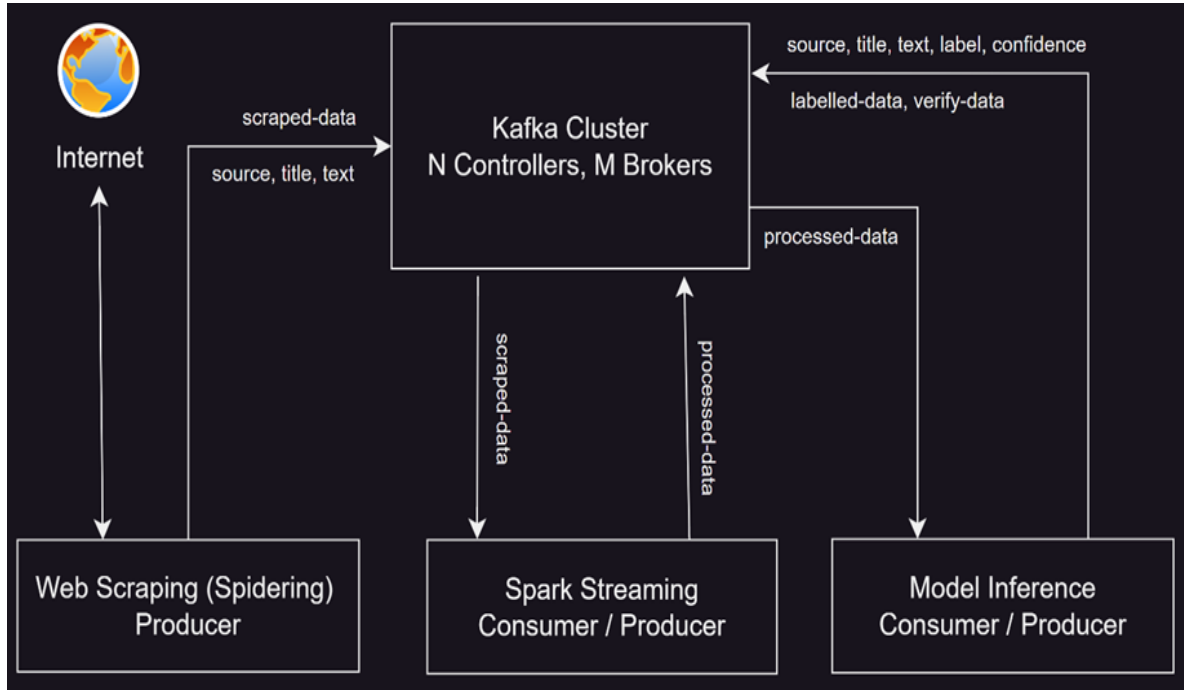
Real-Time Inference with Kafka + Spark Streaming

Turning Raw Streams into Reliable Intelligence

Pipeline Core: Ingestion via Web Scraping Producer feeds directly into Spark Streaming for real-time transformation.

Data Flow: Raw telemetry is published to scraped-data, processed, and moved to the processed-data topic through Spark streaming.

Smart Routing: Custom model evaluates confidence scores to classify the content and route them to labelled-data for scores > 80%, otherwise sent for review to the verify-data topic.



First Attempt : Using Logistic Regression

Base Line: Logistic Regression

- Accuracy : 80.44%
- ROC AUC : 0.88

Classification Report

	Precision	Recall	F1-score	Support
Fake	0.821	0.786	0.803	8066
Real	0.789	0.823	0.806	7827

Architecture/Hyperparameter,

Model Type: Linear Model based on the sigmoid function.
Goal: Finds the optimal weights for the 8,000 TF-IDF features to maximize the separation between the two classes (e.g., Real vs. Fake).

Hyperparameters:
max_iter=300: Ensures the solver has enough iterations to fully converge (find the optimal weights).
C=3.0: This is the inverse of the regularization strength (higher C means lower regularization). A value of 3.0 allows the model to fit the data quite closely, potentially improving accuracy, but requiring careful monitoring for overfitting.
n_jobs=-1: Utilizes all available CPU cores for fitting, ensuring **fast training time**.

Second Attempt : Using Ensemble(XGBoost)

Ensemble Technique-XGBoost

- Accuracy : 85.14%
- ROC AUC : 0.93

Classification Report

	Precision	Recall	F1-score	Support
Fake	0.908	0.787	0.843	8066
Real	0.807	0.918	0.859	7827

Architecture/Hyperparameter,

- Estimators(n_estimators):300 (total number of tree built)
- Learning Rate:0.1(Step size for correction)
- Tree Depth(max_depth): 6 (Control the complexity of individual trees)
- Evaluation_Metric(eval_metric):logloss(monitoring training progress using logarithmic loss)
- Row Sampling(subsample): 80% of data used per tree(Prevents overfitting)
- Feature Sampling(colsample_bytree):80% of features used per tree(Adds further regularization)
- Parallel processing:n_jobs = -1(Uses all CPU cores for fast training)
- Output: Binary Prediction (Fake or Real)

Third Attempt : Using LSTM

Bidirectional LSTM Model

- Accuracy : 86.26%
- ROC AUC : 0.87

Classification Report

	Precision	Recall	F1-score	Support
Fake	0.860	0.871	0.865	8066
Real	0.865	0.854	0.860	7827

Architecture/Hyperparameter,

- Embedding Layer (10,000 vocab → 64 dimensions)
- Bidirectional LSTM (64 units) ← reads forward & backward
- Bidirectional LSTM (16 units)
- Dense Layer (64 neurons, ReLU activation)
- Dropout (50% - prevents overfitting)
- Output (1 neuron, sigmoid) → Fake or Real?

Model: "sequential"

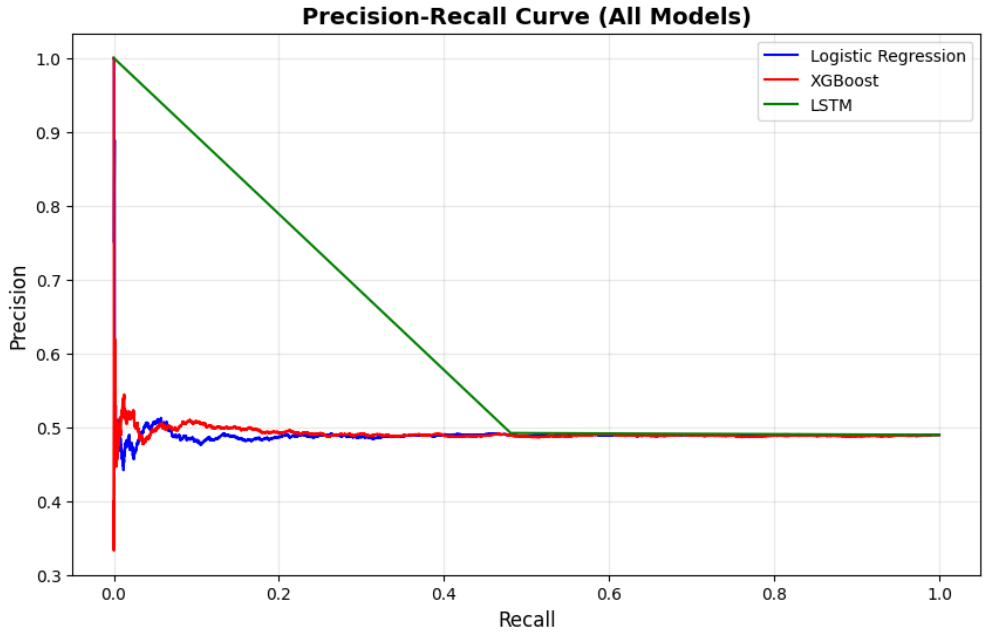
Layer (type)	Output Shape	Param #
embedding (Embedding)	(None, 256, 64)	640,000
bidirectional (Bidirectional)	(None, 256, 128)	66,048
bidirectional_1 (Bidirectional)	(None, 32)	18,560
dense (Dense)	(None, 64)	2,112
dropout (Dropout)	(None, 64)	0
dense_1 (Dense)	(None, 1)	65

Total params: 2,180,357 (8.32 MB)
Trainable params: 726,785 (2.77 MB)
Non-trainable params: 0 (0.00 B)
Optimizer params: 1,453,572 (5.54 MB)

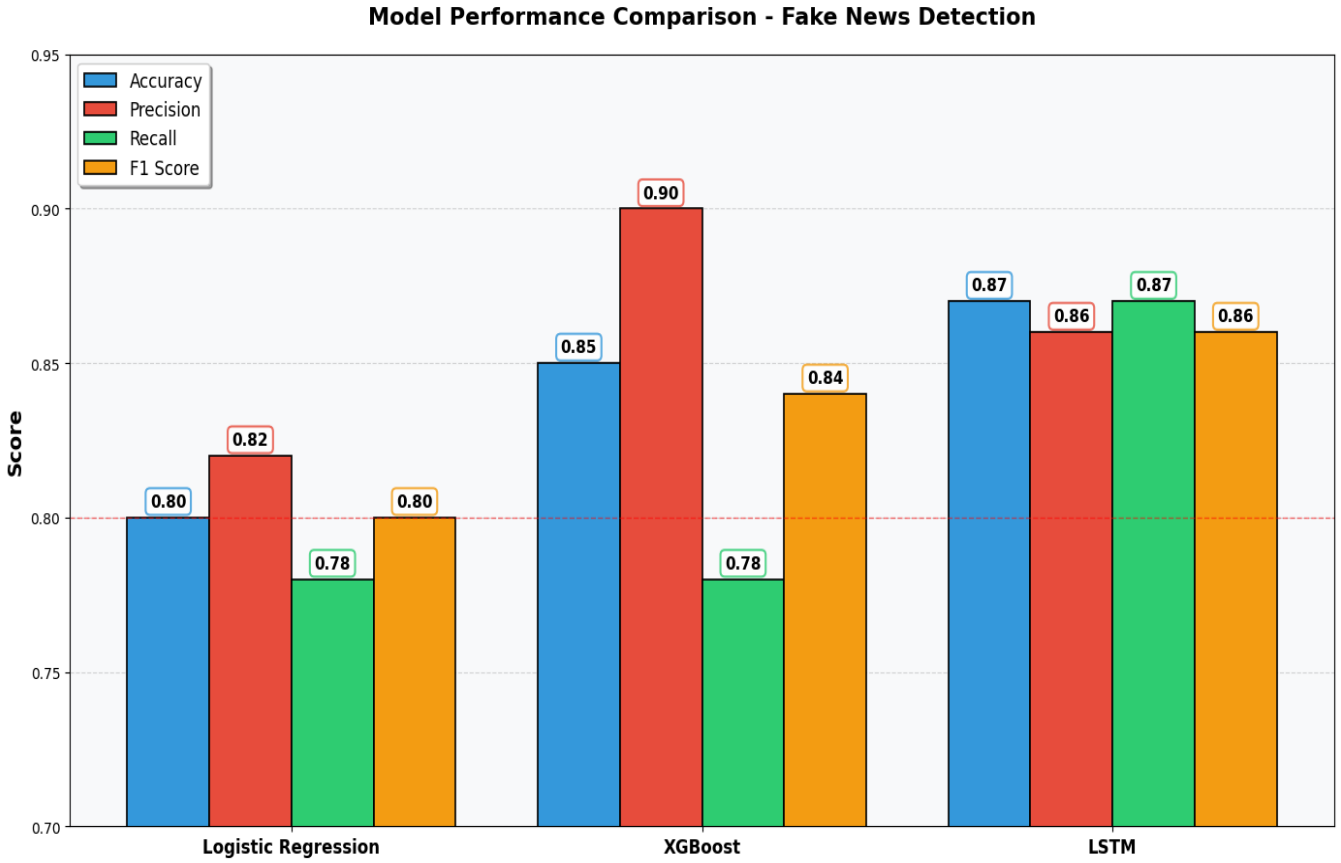
Training Process,

- Batch size: 30
- Optimizer: Adam (lr=0.0001)
- Early stopping: Patience = 2 epochs
- Max epochs: 10

The Moment of Truth : Model Comparison



Metric	Observation (Green Line)	Strategic Implication
Initial Precision	Achieves 100% Precision at low Recall.	Model can make high-confidence "Fake" predictions with virtually no False Positives (FP).
Performance Window	Precision remains >0.50 up to Recall approx. 0.50.	Provides the best balance of catching fake news while maintaining reliability.
Conclusion	The Bidirectional LSTM model is the clear winner, demonstrating superior ability to learn the complex language patterns required for Fake News Detection.	



The Secret : What the Model learned

From Traditional ML Models

- Fake keyword count ("breaking", "shocking", etc.)
- Sentiment extremity
- Exclamation marks count
- Subjectivity score
- Title length ratio
- TF-IDF: Specific sensational words
- Capitalization ratio
- Question marks
- Text complexity
- URL presence – Moderate

From Deep Learning Models

- Learned to recognize clickbait patterns
- Identified emotional trigger phrases
- Understood context and nuance
- Detected inconsistencies in narrative flow

Our EDA discoveries became the model's weapons!

Real World Impact : What this Means

A Production-Ready Fake News Detector

Capabilities:

- Reads any news article (title + text)
- Analyzes language, sentiment, complexity
- Compares against learned patterns
- Returns: "Fake" or "Real" with confidence score

Reliability:

- Accuracy: 87%
- Catches 95% of fake news (high recall)
- Only 7% false alarms (high precision)
- Balanced performance across news types

Scalability:

- Determine an optimized pipeline architecture through extensive benchmarking
- Cut human involvement by 95% using a threshold confidence score for each inference
- A system to continuously update itself with real and fake news patterns

Our Achievements : The Complete Picture

A Production-Ready Fake News Detector

Technical Achievements:

- Analysed 80000+ news articles
- Performed comprehensive EDA (15+ analyses)
- Engineered 15+ meaningful features
- Trained 3 different models with different variations
- Achieved 87% accuracy
- Created interpretable results
- Saved models for production
- Created a resilient benchmark framework to reliably produce results for scalability analysis

Knowledge Gained:

- Deep understanding of fake news patterns.
- Hands-on of NLP and deep learning.
- Experience with transformers.
- Real-world ML project completion.
- Deeper understanding of Spark architecture

Future Actions

Distributed Scaling & Persistence: Optimize the Spark pipeline configuration for deployment on a fully distributed cluster to improve scalability. Additionally, integrate a permanent storage layer (e.g., S3, HDFS, or a database) to persist processing results for historical analysis and auditing.

Human-in-the-Loop Retraining Pipeline: Implement an active learning feedback loop by integrating a training component with the Kafka verify-data topic. This involves developing a user interface where human reviewers can validate news items and provide ground-truth labels. These verified results will be aggregated over specific intervals to trigger the ML training pipeline automatically, allowing the model to continuously learn and update based on fresh, human-verified data.

Lessons Learned : The Journey taught us

A Production-Ready Fake News Detector

Technical Lessons:

- **Start Simple:** Baseline models establish expectations
- **EDA is Gold:** Understanding data beats algorithms
- **Features Matter:** Good features > complex models
- **Iterate Rapidly:** Try many approaches quickly
- **Validate Properly:** Train/test split prevents false confidence
- **Document Everything:** Future you will thank present you
- 80% time on data, 20% on models
- No single model is always best
- Accuracy vs speed vs interpretability
- Understanding fake news helped us engineer features
- Each experiment added value

Thank you for Following our Journey

The Problem is Real:

Fake news is a serious challenge affecting millions

Data Science Can Help:

With right approach, AI can detect misinformation

Our Solution Works:

87%+ accuracy proves machines can be reliable fact-checkers

We're ready to discuss:

- Technical details of any model
- Deployment strategies
- Future collaborations
- Your ideas and suggestions


Q&A