Speaker Verification using Machine and Deep Learning Approaches on the VoxCeleb Dataset

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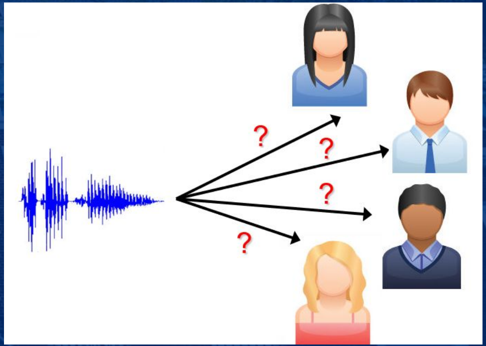


Introduction

Speak Verification:

- recognize who is speaking from a clip of audio recordings accurately.

Importance:

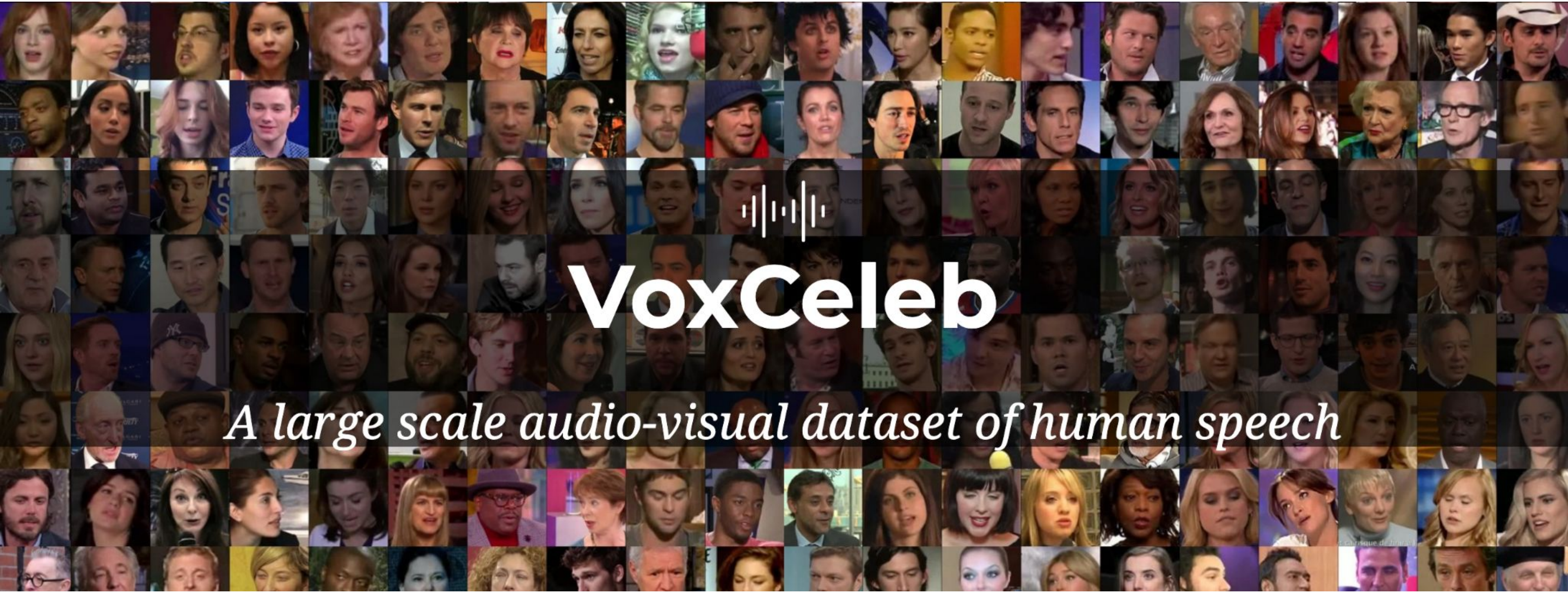
- Device unlocking, Touchless control, create personalization, etc.
- huge real-world usage with a focus on security and usability.

Project Goal

- Build >1 models that can accurately recognize who is speaking from audio recordings

- Compare the performance of traditional Machine Learning and Deep Learning approaches

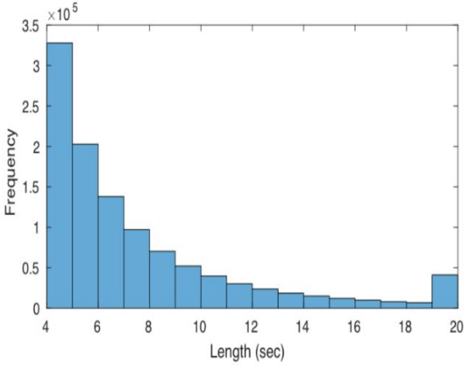
Dataset Overview: VoxCeleb



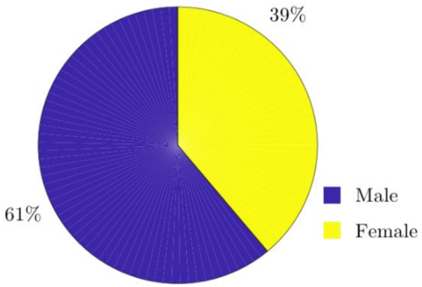
Dataset Overview

Key Features:

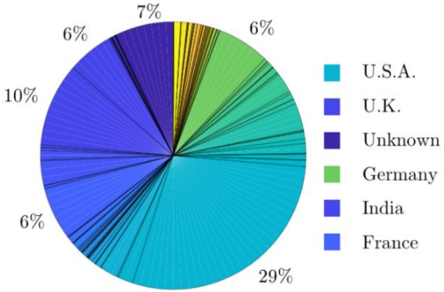
- Diversity and scale
- Real-world noises and variability
- Rich features: opportunity for preprocessing



Utterance Lengths



Gender Distribution



Nationality Distribution

Data Preprocessing

- **Normalization**
- resample to 16 kHz
  - maintain uniform time resolution
- trimmed to remove silence and background noise
  - focus on speech segments

- 100-120 audio clips per speaker
- every audio clip is 4-6 seconds

Feature Extraction

For traditional ML models:

- **Pitch**: Mean and standard deviation of fundamental frequency (f0)
- **Mel-Frequency Cepstral Coefficients (MFCCs)**: 13 Mel-Frequency Cepstral coefficients and their deltas.
- **Spectral Features**: Centroid, contrast, and chroma.
- **Energy, Zero-Crossing Rate (ZCR)**: Capture signal dynamics.

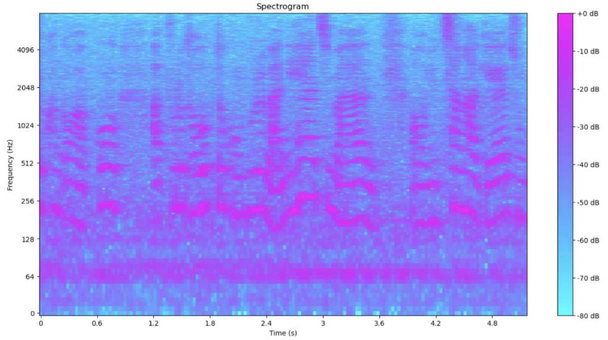
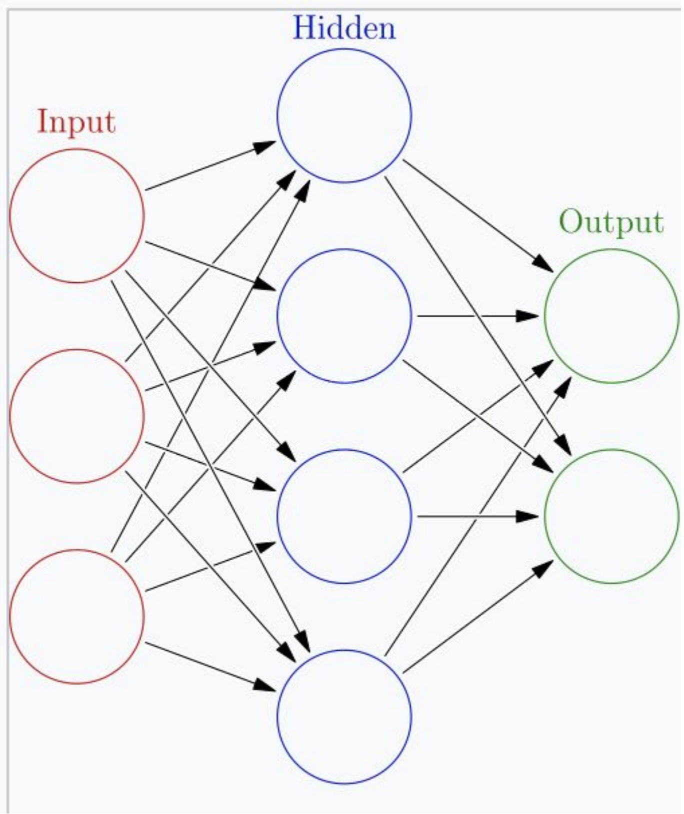


Figure 1: A spectrogram representation of an audio segment

Feature Extraction

For DL models:

- Direct use of raw audio or log-Mel spectrograms.
- hand-crafted features (YAMNet)



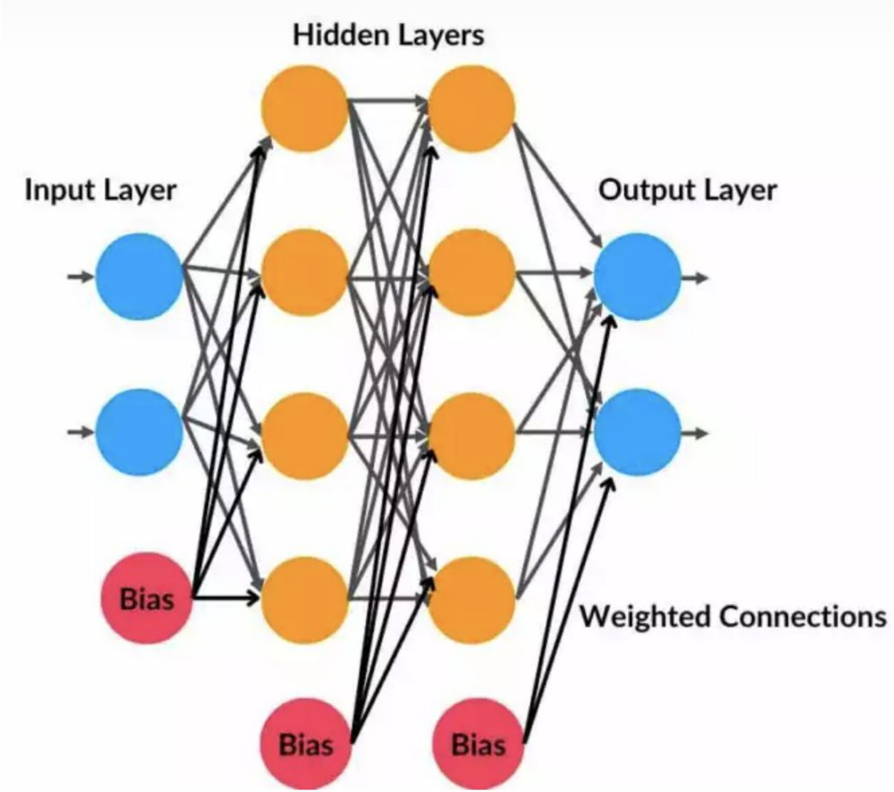
Methodology: ML Models

1. **Naive Bayes**
2. **Logistic Regression**
3. **Support Vector Machines (SVM):**
   - Kernels: Linear, RBF.
   - Tuned Parameters using grid search: C (regularization), γ (kernel coefficient).
4. **Random Forest:** Decision trees optimized for depth and estimators.
5. **XGBoost:** Advanced tree-based model

Methodology: DL Models

Three Multilayer Perceptron (MLP) Architectures:

- SmallNet (2 layers), MediumNet (3 layers), LargeNet (4 layers).
- trained from scratch using extracted embeddings.



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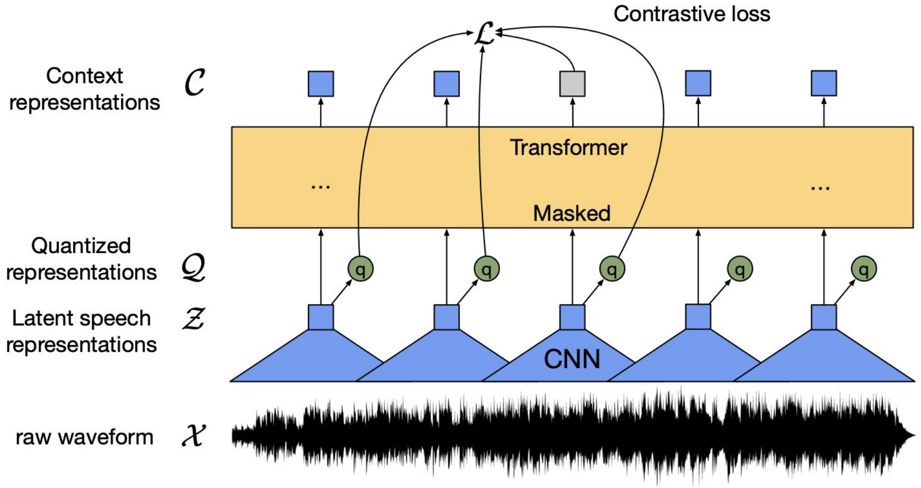
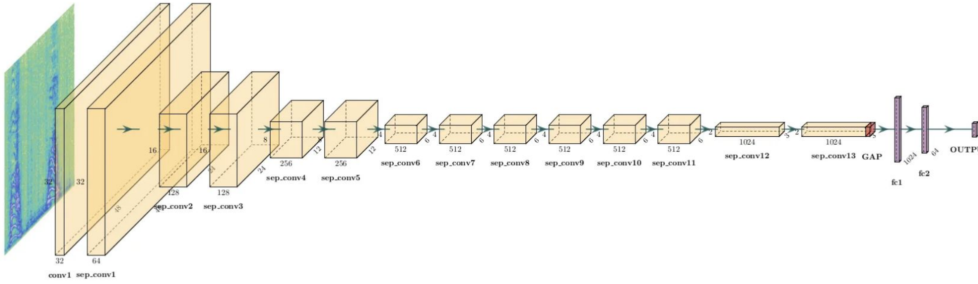
Methodology: DL Models

Pre-trained Models (on 200-speaker subset):

- Wav2Vec: Fine-tuned for speaker classification.
- YAMNet: Adapted from sound event detection to speaker tasks.





Evaluation Metrics

Accuracy:

- % of correctly classified samples.
- Primary metric for comparison.

Training Time:

- Qualitative

We balances clarity in comparisons and real-world feasibility.

Experiment Setup

Dataset: VoxCeleb (200-speaker subset used for consistency).

Data split: 80% training, 20% testing (no speaker overlap).

Inputs:

- **ML**: Hand-crafted features (e.g., MFCCs, ZCR).
- **DL**: Raw audio or spectrograms, plus hand-crafted features (YAMNet)

Baseline vs. fine-tuned models tested.

Feature Selection

```
=== Trying threshold: 0.01 ===
Number of features selected: 39
Selected features: [4, 36, 14, 6, 10, 12, 17, 22, 5, 1, 2, 15, 3, 0, 23, 7, 11, 9, 8, 16, 38
, 21, 30, 29, 18, 20, 27, 13, 31, 19, 28, 33, 34, 24, 25, 26, 32, 35, 37]
Cross-validated accuracy: 0.4757 ± 0.0640

=== Trying threshold: 0.015 ===
Number of features selected: 29
Selected features: [4, 36, 14, 6, 10, 12, 17, 22, 5, 1, 2, 15, 3, 0, 23, 7, 11, 9, 8, 16, 38
, 21, 30, 29, 18, 20, 27, 13, 31]
Cross-validated accuracy: 0.4741 ± 0.0662

=== Trying threshold: 0.02 ===
Number of features selected: 22
Selected features: [4, 36, 14, 6, 10, 12, 17, 22, 5, 1, 2, 15, 3, 0, 23, 7, 11, 9, 8, 16, 38
, 21]
Cross-validated accuracy: 0.4685 ± 0.0670

=== Trying threshold: 0.025 ===
Number of features selected: 16
Selected features: [4, 36, 14, 6, 10, 12, 17, 22, 5, 1, 2, 15, 3, 0, 23, 7]
Cross-validated accuracy: 0.4365 ± 0.0611
```

Selected Features:

All features except

- Zero center rate
- energy

Machine Learning Results

Model	Validation Accuracy (%)
Naive Bayes	17.56
Logistic Regression	23.99
Support Vector Machine (SVM)	28.71
Random Forest	25.47
XGboost	25.20

Table 1: Models Performance with traditional 3 audio features

Machine Learning Results

Model	Validation Accuracy (%)
Naive Bayes	24.15
Logistic Regression	36.41
Support Vector Machine (SVM)	37.61
Random Forest	33.83
XGboost	35.35

Table 3: Models Performance with newly added features

Machine Learning Results

Hyperparameter Optimization

- After extensive tuning,

  optimized **Random Forest** achieved **33.83%** accuracy
- Key tuned parameters:
  - N estimators: 100
  - Max depth: 50
  - Min sample split: 2
  - Min sample leaf: 1

Machine Learning Results

Hyperparameter Optimization

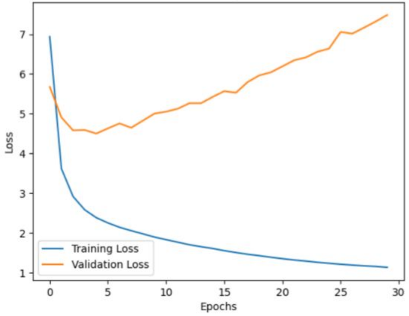
- After extensive tuning,

  optimized **XGBoost** achieved **35.35%** accuracy
- Key tuned parameters:
  - Learning rate: 0.05
  - Max depth: 10
  - Estimators: 1000
  - Subsample: 0.4

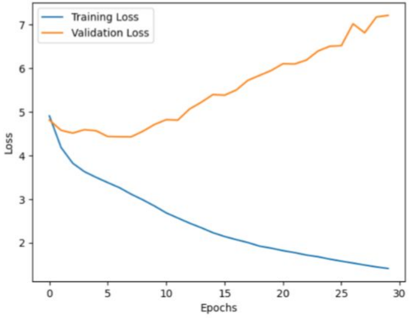
Deep Learning Results

MLP Models (predefined features)

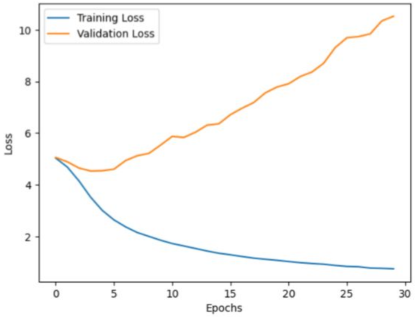
Model	Training Accuracy	Val. Accuracy	Training Speed
SmallNet	69.94%	21.99%	1.08s/epoch
MediumNet	63.83%	20.48%	1.29s/epoch
LargeNet	78.49%	21.17%	1.57s/epoch



(a) SmallNet



(b) MediumNet

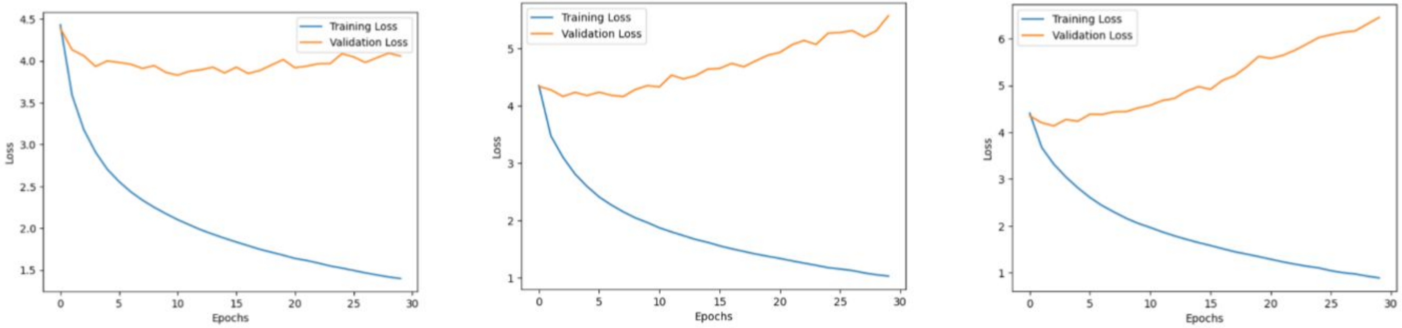


(c) LargeNet

Deep Learning Results

YAMNet:

Model	Training Accuracy	Val. Accuracy	Training Speed
SmallNet	64.45%	23.91%	1.21s/epoch
MediumNet	70.88%	21.40%	1.36s/epoch
LargeNet	74.09%	20.08%	1.49s/epoch

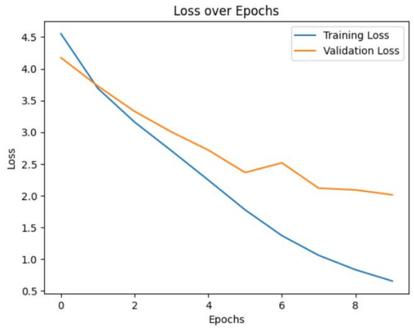


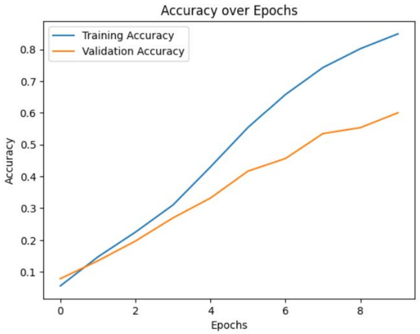
(a) SmallNet (b) MediumNet (c) LargeNet

Deep Learning Results

Fine-Tuned Models

- **Wav2Vec**:
  - Training: 84.92%; Validation: 60.03%. (Took about 7 hours (3.8 iterations per second) to train the model for 10 epochs)





- **HuBERT**: Not fine-tuned; high computational cost.
  - One iteration is ≈ 17 seconds for a batch of two audio clips, equivalent to 203 hours for an epoch.

Overall Performance Comparison

Deep Learning Outperforms Traditional Machine Learning

- Wav2Vec Model: Validation Accuracy: 60.03%
- Best ML Model (SVM): Validation Accuracy: 37.61%

Performance Gap:

- DL models effectively capture complex speaker-specific features.
- Traditional ML relies on on manually designed features (MFCCs, ZCR)

Computational Considerations

Traditional ML Models:

- Hardware: Trained on Apple M2 Pro CPU
- Pros: Quick training iterations, low resource requirements

Deep Learning Models:

- Hardware: Trained on AMD Ryzen 5900X CPU & NVIDIA RTX 3060 GPU
- Cons: Higher computational demands, longer training times

Conclusion, Future Work

DL models (Wav2Vec) outperform ML in speaker verification.

ML still works for lightweight applications.

Future Directions:

- Making deep learning methods more resource-efficient.
- Optimize training pipelines to reduce computational overhead without losing performance. (Pre-process and cache audio features)

Thank You!
Any Questions?

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