

Empowering the Oil and Gas Industry with Generative AI

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الدكتور مراد بوعاش

الذكاء الاصطناعي كهرباء المستقبل

المنهف

الضريح الملكي الموريطاني - تيبازة

Exemples d'applications

- Calculs mathématiques.
- Traitement de texte.
- Automatisation de tâches simples.
- Applications web basiques.

```
[ ] def calculer_moyenne(notes):
    total = sum(notes)
    moyenne = total / len(notes)
    return moyenne

notes = [15, 18, 12, 16]
moyenne = calculer_moyenne(notes)
print("La moyenne est:", moyenne)
```

Exemples d'applications IA

- Reconnaissance d'images et de la parole.
- Traduction automatique.
- Chatbots et assistants virtuels.
- Recommandation de produits.
- Analyse de sentiments.

```
[ ] from sklearn.feature_extraction.text import TfidfVectorizer
    from sklearn.svm import SVC
    from sklearn.pipeline import make_pipeline

    # Données d'entraînement
    X_train = ["Ceci est un texte positif", "Un autre texte positif", "Texte négatif", "Encore un texte négatif"]
    y_train = ["positif", "positif", "négatif", "négatif"]

    # Modèle
    model = make_pipeline(TfidfVectorizer(), SVC())
    model.fit(X_train, y_train)

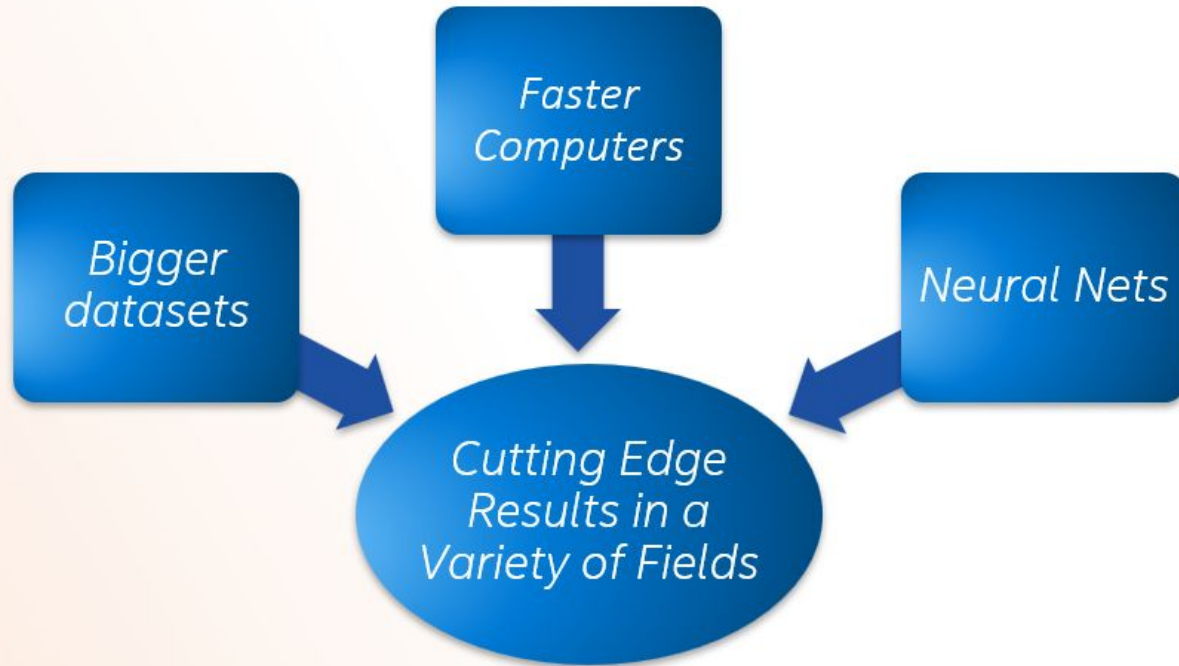
    # Prédiction
    text_a_classifier = "Ceci est un nouveau texte"
    prediction = model.predict([text_a_classifier])
    print("Sentiment prédit:", prediction[0])
```

The difference ...

Caractéristique	Programme Traditionnel	Programme avec IA
Mode de fonctionnement	Instructions explicites	Apprentissage à partir de données
Structure du code	Fonctions, classes	Bibliothèques d'IA
Types d'applications	Tâches bien définies	Tâches complexes, ambiguës
Avantages	Prévisible, rapide	Apprentissage, adaptabilité
Inconvénients	Moins flexible	Données, biais, interprétabilité

AI in the Modern Era

Faster hardware is one of the key areas driving the modern era of AI.



End-to-End Computing for AI



DATACENTER

Many-to-many hyperscale,
for stream and massive batch data processing

Ethernet
& Wireless



GATEWAY

1-to-many,
majority streaming data from devices

Wireless & non-IP wired,
secure, high throughput, real-time



EDGE

1-to-1 devices,
lower power and UX requirements

Déluge de données

En **2020**, nous avons assisté à un véritable déluge de données, avec un flux moyen de **1,5 Go par jour**.

Plusieurs facteurs contribuent à cette croissance exponentielle du volume de données :

- L'essor de l'Internet des Objets (IoT)
- L'utilisation accrue des médias sociaux
- La multiplication des contenus numériques

Prédictions pour 2024 et 2025

- **2024**: On estime que le flux quotidien moyen de données pourrait atteindre 5,76 Go.
- **2025**: Ce chiffre pourrait grimper jusqu'à 8,06 Go par jour.



BY 2020

AVG. INTERNET USER **1.5 GB** OF TRAFFIC / DAY

AUTONOMOUS VEHICLES **4 TB** OF DATA / DAY

CONNECTED AIRPLANE **5 TB** OF DATA / DAY

SMART FACTORY **1 PB** OF DATA / DAY

CLOUD VIDEO PROVIDERS **750 PB** OF VIDEO / DAY

**THE COMING
FLOOD OF DATA**

AI TIMELINE: 1947-2020

1947

Alan Turing talks about AI in London

1966

MIT releases the ELIZA chatbot

2011

IBM Watson beats players on *Jeopardy!*

2015

AlphaGo beats Fan Hui

1940s

1950s

1960s

1970s

1980s

1990s

2000s

2010s

1950

Turing's papers on *Intelligent machines*

1997

Deep Blue beats Garry Kasparov in chess

2017 Google Transformer

2018 GPT-1 117M

2019 GPT-2 1.5B



2020



Jan

Google Meena 2.6B

May

GPT-3 175B

Jun

iGPT 6.8B

Sep

GPT-3 writes newspaper column

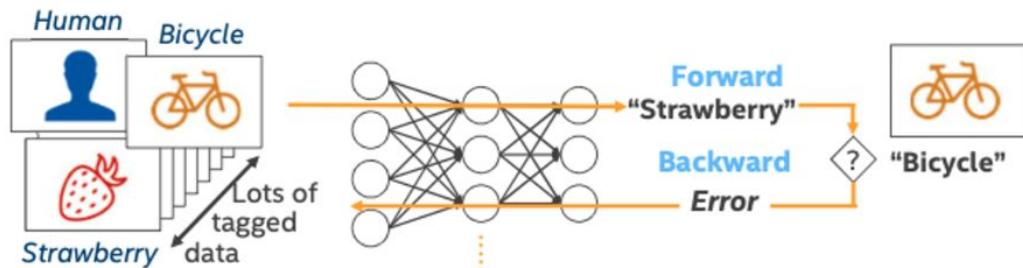
WHAT IS AI?

AI

MACHINE
LEARNING

DEEP
LEARNING

TRAINING:



INFERENCE:

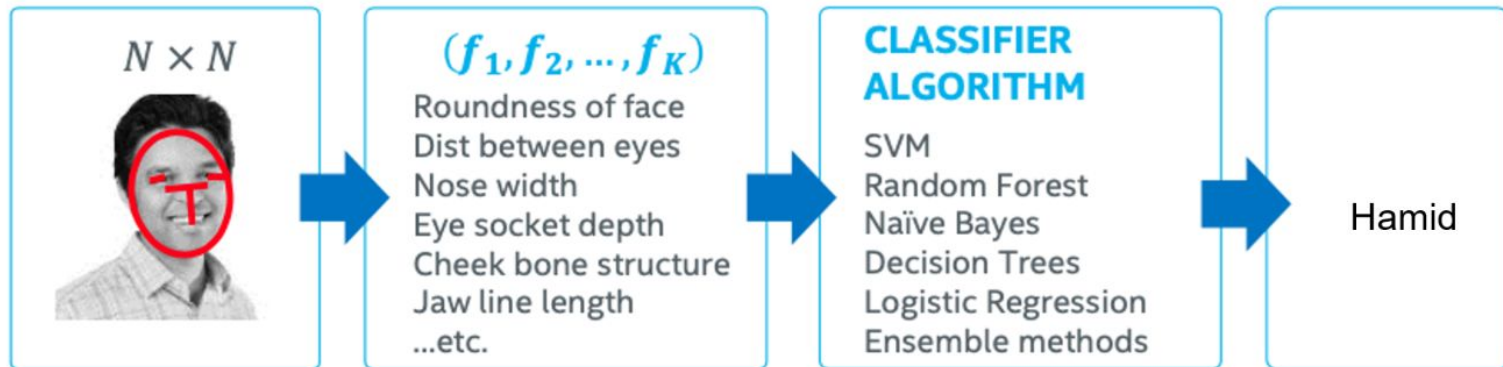


MANY DIFFERENT APPROACHES TO AI

MACHINE VS. DEEP LEARNING

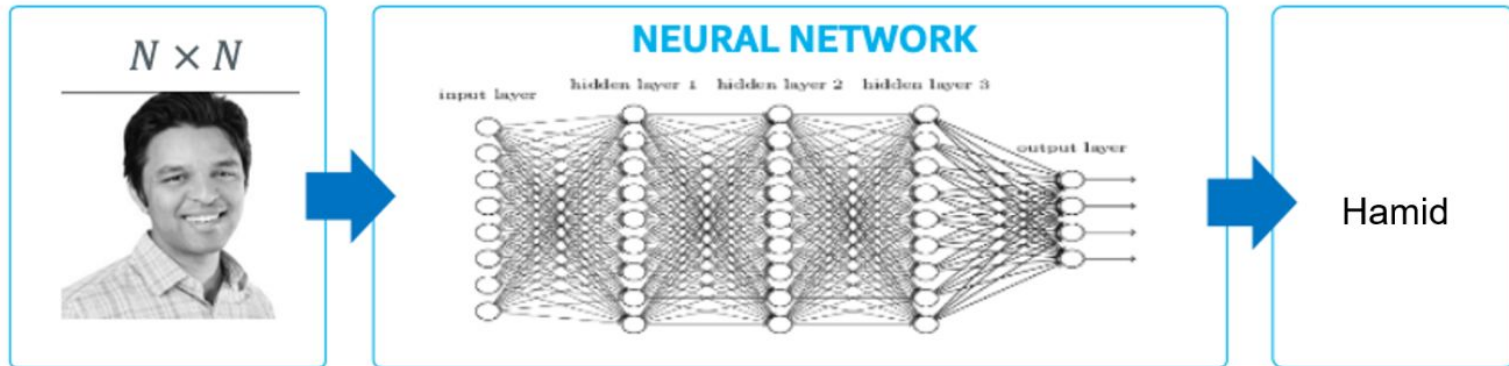
MACHINE LEARNING

How do you engineer the best features?



DEEP LEARNING

How do you guide the model to find the best features?



NATIONAL BESTSELLER

WHEN COMPUTERS EXCEED
HUMAN INTELLIGENCE

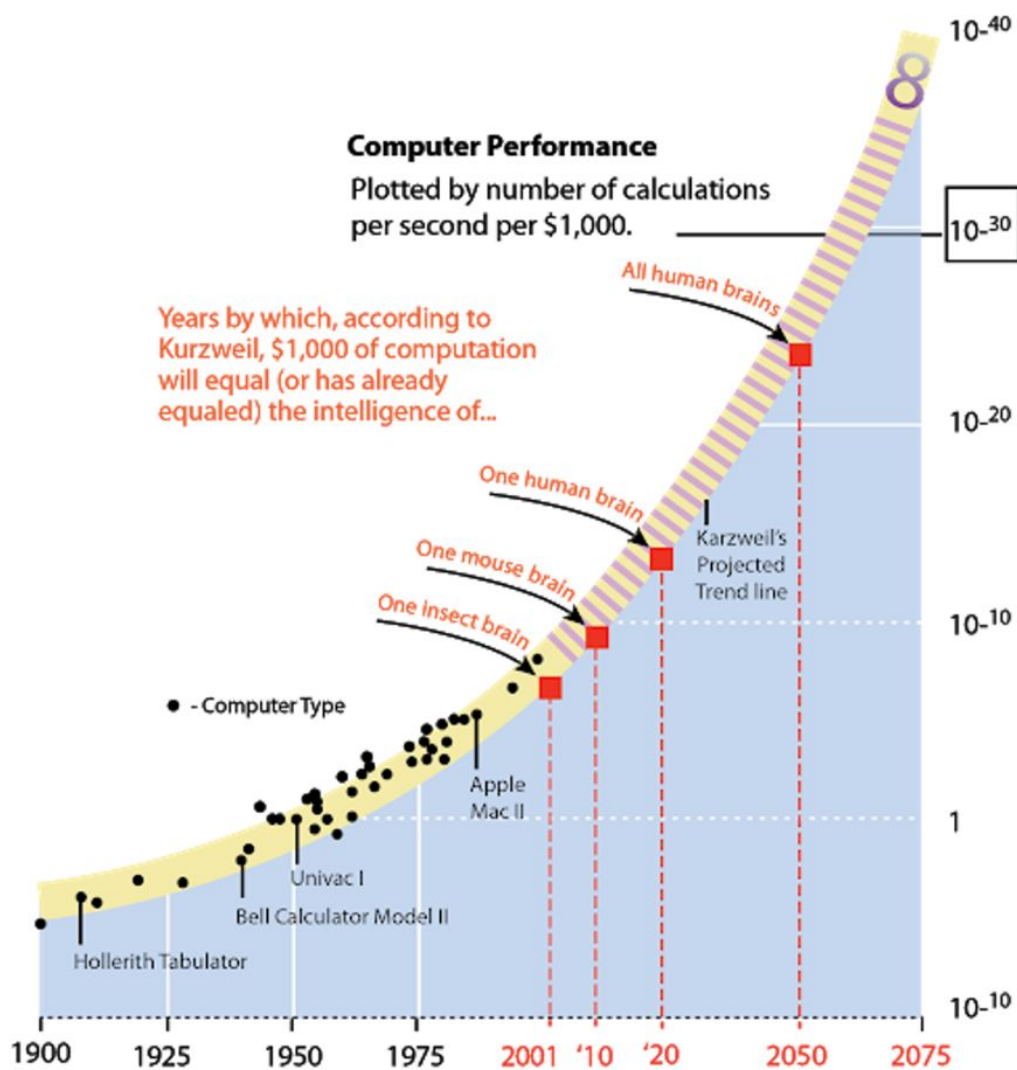
THE AGE OF SPIRITUAL MACHINES



RAY KURZWEIL

AUTHOR OF *THE AGE OF INTELLIGENT MACHINES*

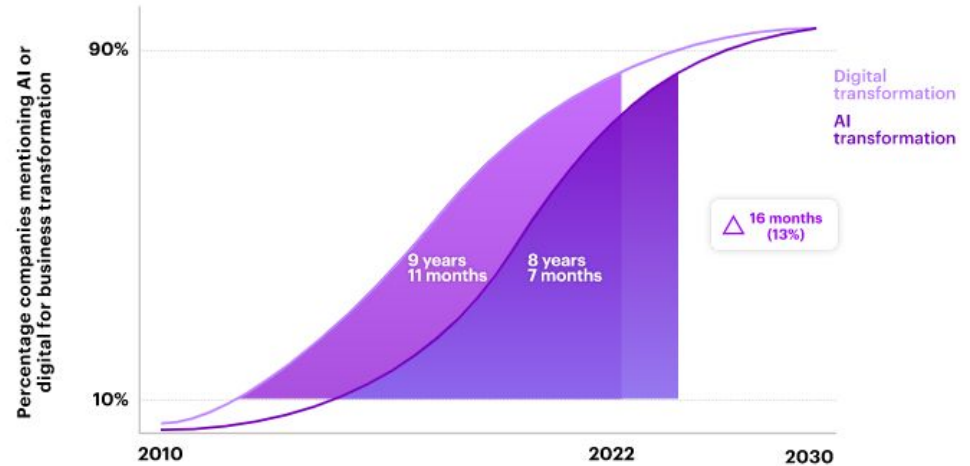
"The Age of Spiritual Machines will blow your mind. Kurzweil lays out a scenario that might seem like science fiction if it weren't coming from a proven entrepreneur."
— *San Francisco Chronicle*



AI transformation will take less time than digital transformation

La transformation par l'intelligence artificielle (IA) est en passe de s'opérer plus rapidement que la transformation numérique.

- **L'IA s'appuie sur les fondations du numérique**
- **L'IA est plus mature qu'on ne le pense**
- **Les bénéfices de l'IA sont plus tangibles**
- **La concurrence pousse à l'adoption de l'IA**



Source: Accenture Research.

AI WILL TRANSFORM



CONSUMER

HEALTH

FINANCE

RETAIL

GOVERNMENT

ENERGY

TRANSPORT

INDUSTRIAL

OTHER

Smart Assistants
Chatbots
Search
Personalization
Augmented Reality
Robots

Enhanced Diagnostics
Drug Discovery
Patient Care
Research
Sensory Aids

Algorithmic Trading
Fraud Detection
Research
Personal Finance
Risk Mitigation

Support Experience
Marketing
Merchandising
Loyalty
Supply Chain
Security

Defense
Data Insights
Safety & Security
Resident Engagement
Smarter Cities

Oil & Gas Exploration
Smart Grid
Operational Improvement
Conservation

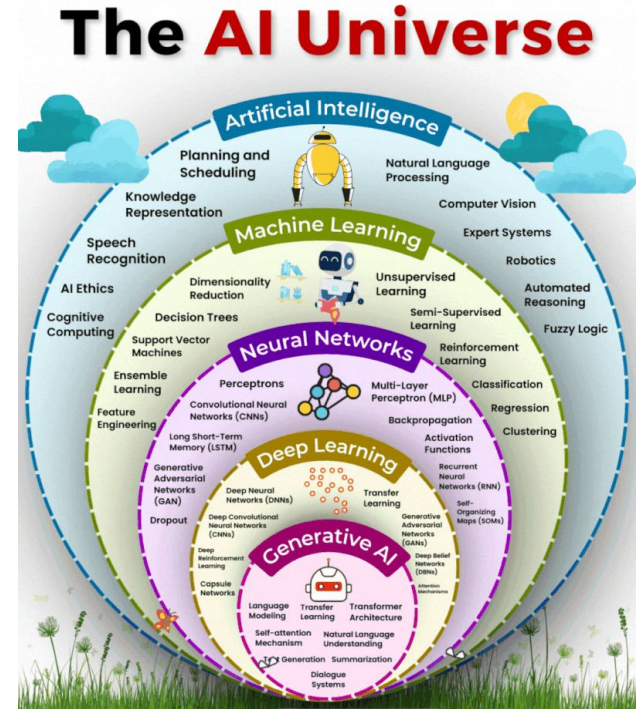
In-Vehicle Experience
Automated Driving
Aerospace
Shipping
Search & Rescue

Factory Automation
Predictive Maintenance
Precision Agriculture
Field Automation

Advertising
Education
Gaming
Professional & IT Services
Telco/Media
Sports

L'Intelligence Artificielle (IA)

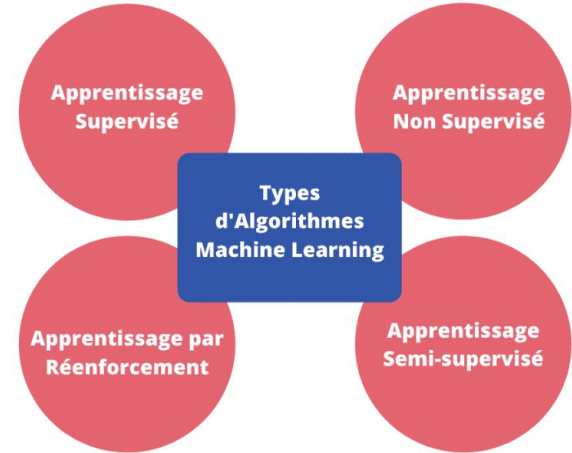
- L'intelligence artificielle (IA) est un domaine de l'informatique qui traite de la création d'agents intelligents.
- L'apprentissage automatique (ML) est un sous-domaine de l'IA. C'est un programme ou un système qui apprend d'un modèle à partir de données d'entrée.
- Le modèle appreni peut faire des prédictions utiles à partir de nouvelles données jamais vues auparavant, tirées des mêmes données utilisées pour entraîner le modèle.

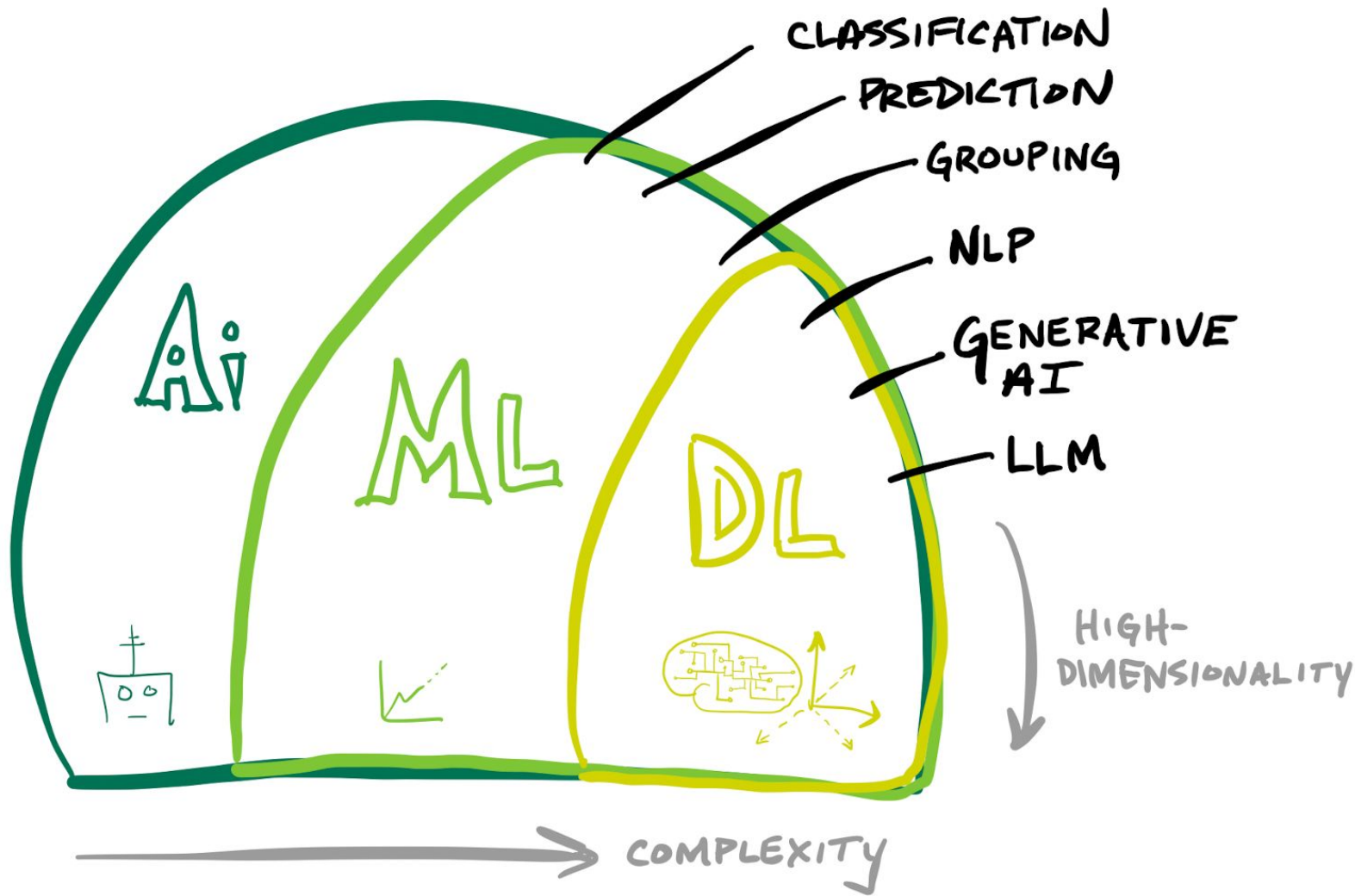


Apprentissage Automatique

Deux types d'apprentissage automatique

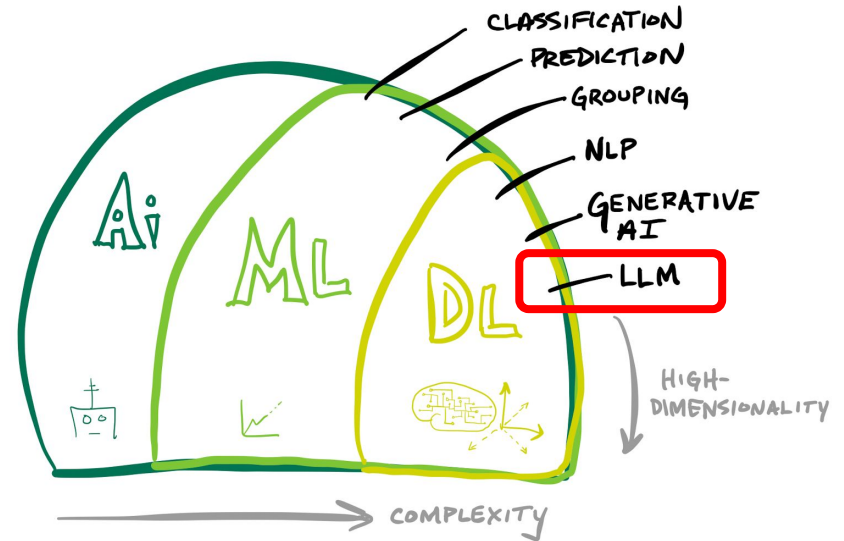
- **L'apprentissage automatique supervisé** utilise des données étiquetées. Les données étiquetées sont des données accompagnées d'une étiquette, comme un nom, un type ou un numéro.
- **L'apprentissage automatique non supervisé** utilise des données non étiquetées. Les données non étiquetées sont des données qui ne sont accompagnées d'aucune étiquette.





LLM (Large Language Model)

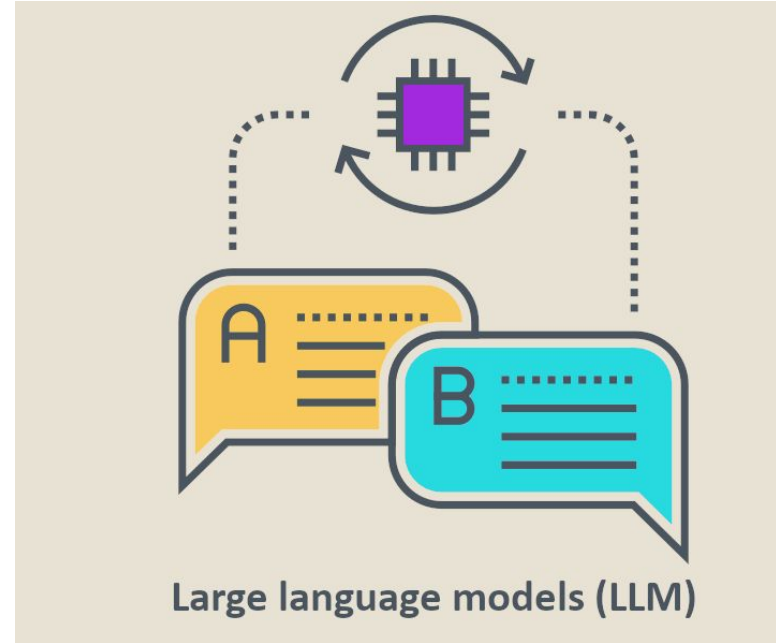
- Les modèles de langage informatique sont un type d'intelligence artificielle (IA) qui peuvent générer du texte, traduire des langues, écrire différents types de contenu créatif et répondre à vos questions de manière informative.
- Ils sont formés sur des quantités massives de données textuelles et sont capables de communiquer et de générer du texte semblable à celui d'un humain en réponse à une large gamme de questions.
- Par exemple, utiliser un LLM pour lui demander de résumer un sujet factuel ou de créer une histoire.



Types de LLM

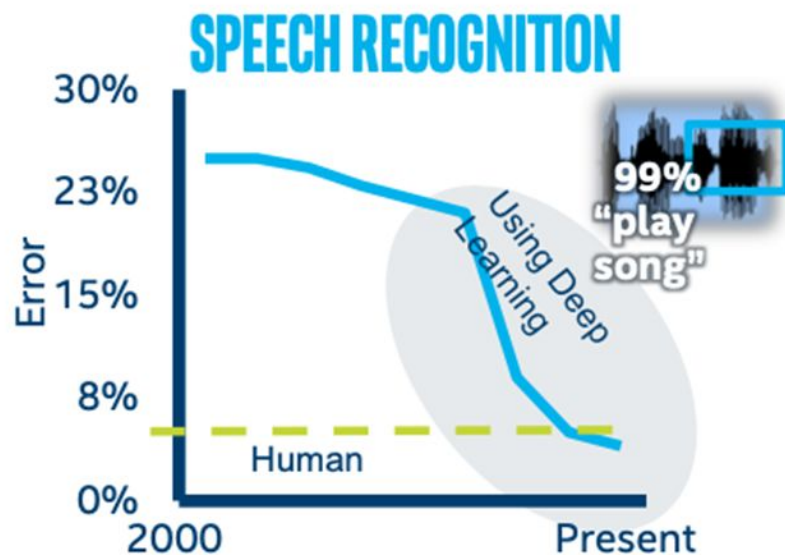
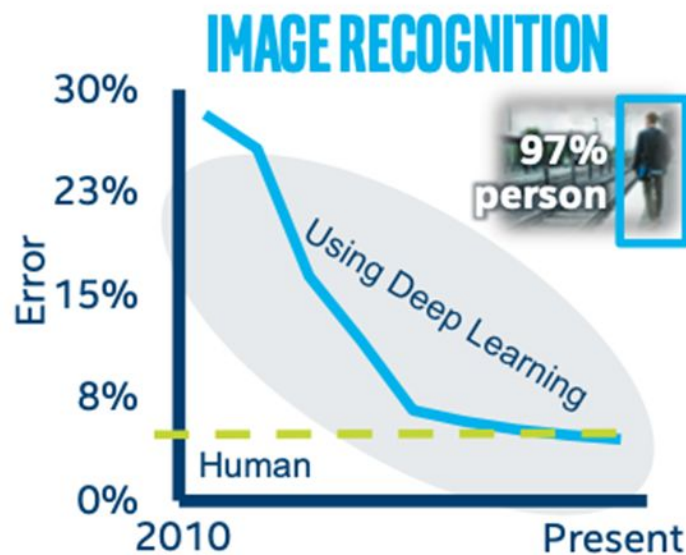
Il existe trois principaux types de LLM : les modèles de langage génériques, les modèles à instructions et les modèles à dialogue.

- **Les modèles de langage génériques** sont formés pour prédire le mot suivant dans une séquence de mots.
- **Les modèles à instructions** sont formés pour suivre des instructions et accomplir des tâches.
- **Les modèles à dialogue** sont formés pour avoir des conversations.



DEEP LEARNING BREAKTHROUGHS

Machines able to meet or exceed human image & speech recognition

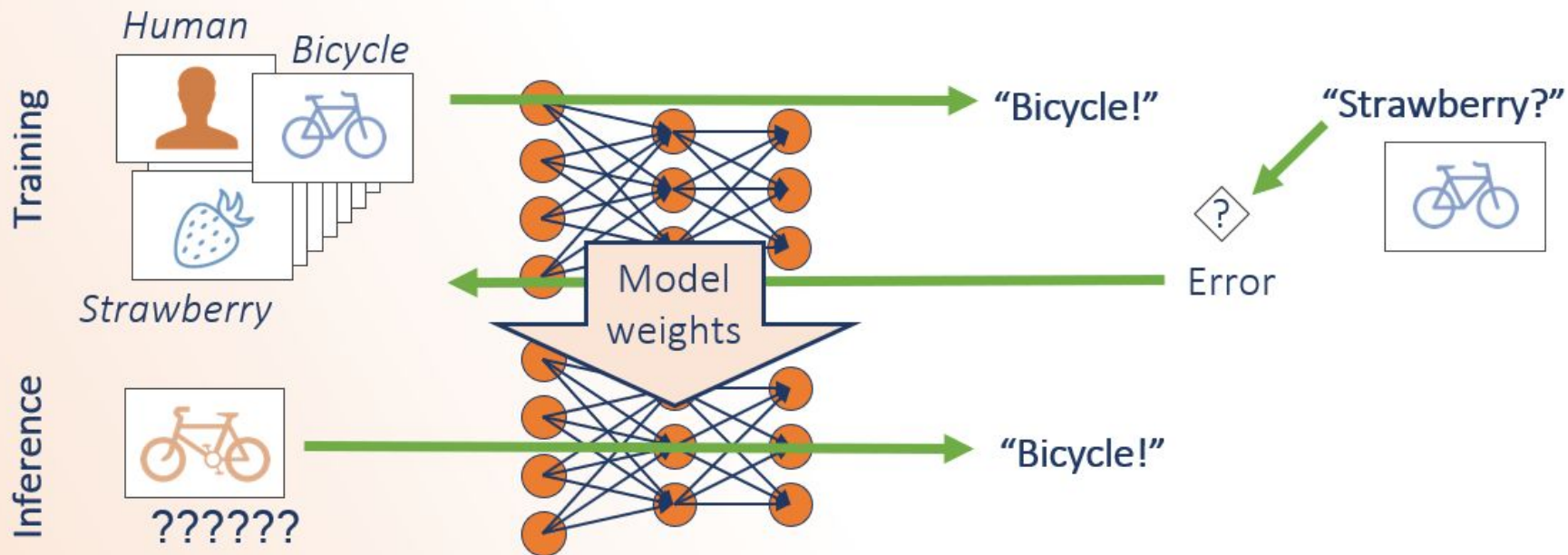


e.g.

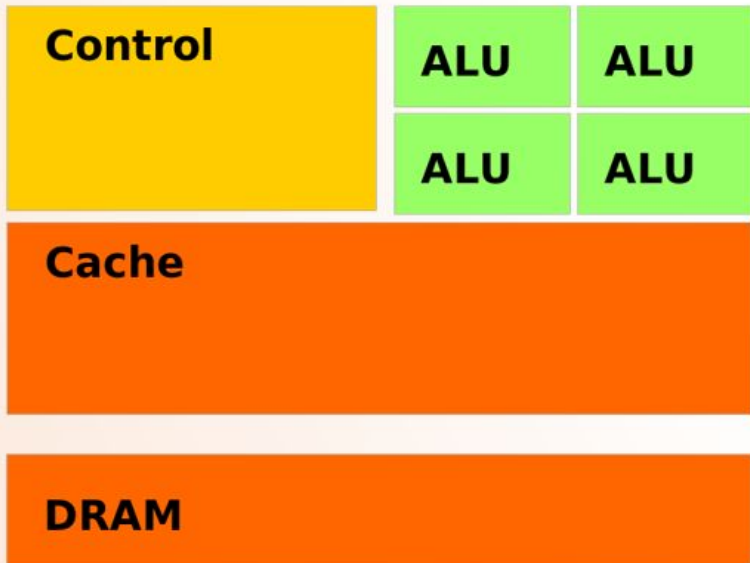


Training vs. Inference

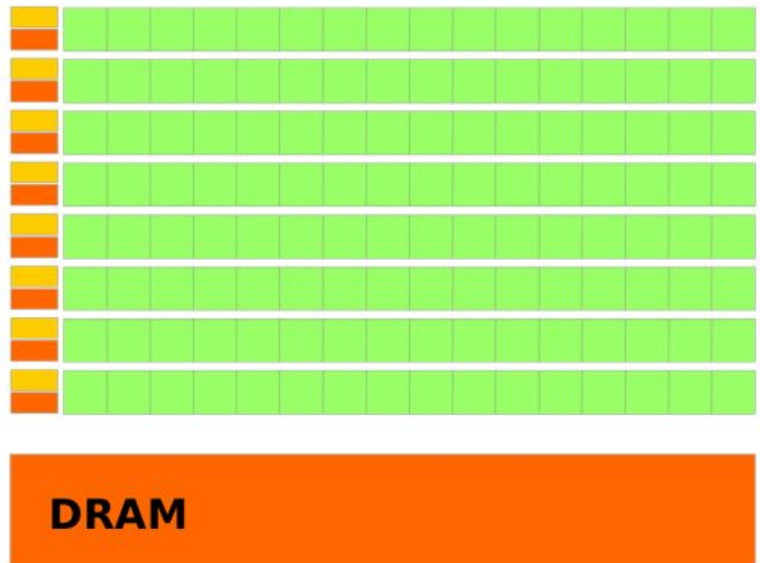
Goal: Perform well on unseen data during inference.



CPUs vs GPUs



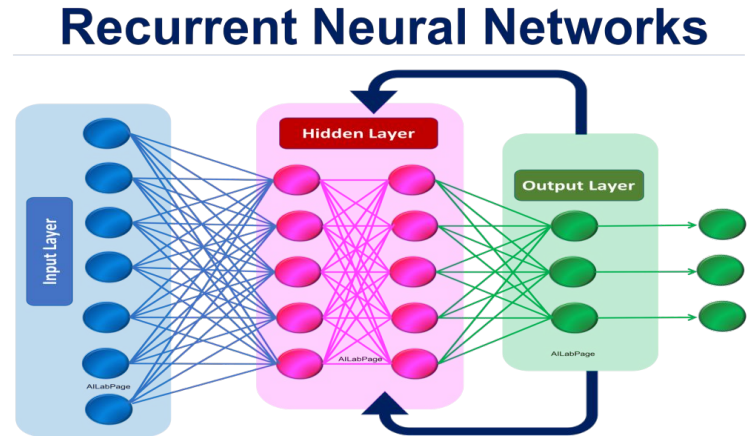
CPU



GPU

Deep Learning Breakthroughs: Oil and Gas

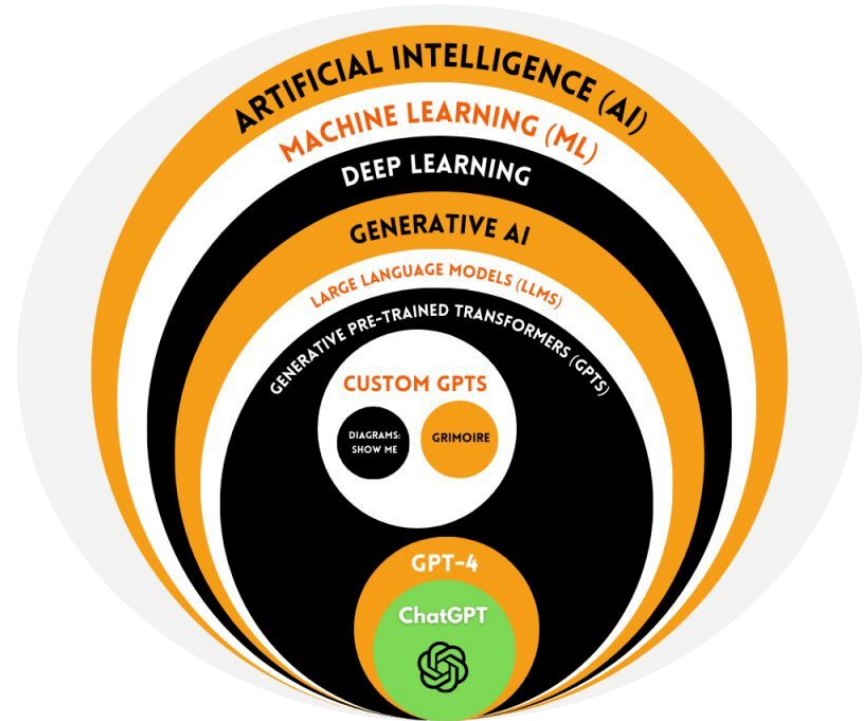
1. **Interprétation sismique redéfinie** : Les réseaux de neurones convolutifs (CNN) déchiffrent les images sismiques avec une acuité sans précédent. Failles, chenaux, réservoirs potentiels, accélérant l'exploration et réduisant les forages à vide.
2. **Production optimisée en temps réel** : Les réseaux de neurones récurrents (RNN) et leurs acolytes modélisent les systèmes de production les plus complexes.
3. **Maintenance prédictive** : Les capteurs des équipements sont les yeux et les oreilles de l'apprentissage profond. Les algorithmes auscultent ces données, prédisant les défaillances avant qu'elles ne surviennent.
4. **Caractérisation des réservoirs** : L'apprentissage profond fusionne les données sismiques, les diagraphies et les historiques de production pour dresser un portrait précis des réservoirs.
5. **Détection d'anomalies**



The evolution of AI

From AI to Generative AI: A Journey of Innovation

- AI: The broad field of making machines intelligent.
- ML: Machines learning from data without explicit programming.
- DL: Machines learning through deep neural networks.
- LLMs: Powerful language models forming the backbone of Generative AI.
- Generative AI: AI that creates new text, images, code, etc.



AI at Intel

TAME YOUR DATA DELUGE
with our data layer expertise



SPEED UP DEVELOPMENT
with open AI software



CHOOSE ANY APPROACH
from analytics to deep learning



DEPLOY AI ANYWHERE
with unprecedented HW choice



SIMPLIFY AI
via our robust community



SCALE WITH CONFIDENCE
on the platform for IT & cloud



Oil and Gas : AI to Optimize Operations

Traditionally : Shrinking oil reserves force companies to operate in remote and possibly hostile areas.

- Price has fallen dramatically in recent years.
- Forcing company layoffs and drastic budget cuts.
- Ultimately, companies are in great need of optimizing operations and cost.



Optimisation des opérations : Traditionnelle vs. IA

- **Expertise humaine** : Les ingénieurs et les géologues prenaient des décisions basées sur leur expérience et leur connaissance du terrain.
- **Modélisation** : Des modèles mathématiques complexes étaient utilisés pour simuler les réservoirs et prédire la production, mais ces modèles étaient souvent simplifiés et ne tenaient pas compte de toutes les variables.
- **Analyse de données** : Les données de production étaient collectées et analysées, mais les outils d'analyse étaient souvent peu sophistiqués et ne permettaient pas d'identifier facilement les tendances et les anomalies.

Plusieurs limites :

- **Dépendance à l'expertise humaine** : Les décisions étaient souvent subjectives et dépendaient de la disponibilité d'experts.
- **Complexité des modèles** : Les modèles étaient difficiles à calibrer et à maintenir à jour.
- **Difficulté à identifier les problèmes** : Les anomalies dans les données de production étaient souvent détectées tardivement.



Oil and Gas : AI to Optimize Operations

Now with AI : AI uses economic, political and weather data to forecast optimum production locations.

- Drilling is still an expensive and risk-prone endeavor.
- ML, with seismic, thermal and strata data, can help optimize the drilling process.



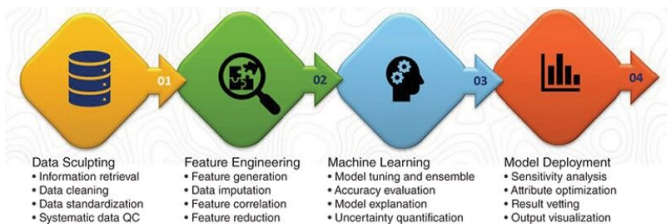
Exemples d'application de l'IA

- **Optimisation du forage** : L'IA peut aider à choisir le meilleur emplacement pour les puits, à optimiser les paramètres de forage et à détecter les problèmes en temps réel.
- **Maintenance prédictive** : L'IA peut prédire les pannes des équipements et permettre une maintenance proactive, réduisant ainsi les temps d'arrêt et les coûts de réparation.
- **Optimisation de la production** : L'IA peut ajuster les paramètres de production en fonction des conditions du réservoir et des prix du marché pour maximiser la rentabilité.
- **Gestion des risques** : L'IA peut identifier les risques opérationnels et environnementaux et aider à mettre en place des mesures de mitigation.



Machine learning-driven drilling optimization

- **Data Collection & Storage:** Historical Drilling Data, Real-Time Data, Storage
- **Data Preprocessing Pipeline:** Cleaning, Feature Engineering, Scaling/Normalization: Standardize feature values for model training.
- **Model Training:** Algorithm Selection, Training, Validation
- **Model Deployment:** Containerization, Cloud Deployment, API Creation
- **Real-Time Feature Engineering:** Process incoming data, Feature Calculation
- **Real-Time Scoring:** Inference, Feedback Loop.



```
[ ] # Libraries
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestRegressor
from sklearn.metrics import mean_squared_error

# 1. Data Loading & Preprocessing (Use appropriate libraries for your data format)
# ...

# 2. Model Training
model = RandomForestRegressor(n_estimators=100, random_state=42)
model.fit(X_train, y_train)

# 3. Model Evaluation
# ... (Similar to the previous code example)

# 4. Well Placement Prediction
def predict_optimal_location(geological_data):
    # ... (Implementation as described in the conceptual diagram)

# 5. Parameter Optimization
def optimize_parameters(current_parameters, real_time_data):
    # ... (Implementation as described in the conceptual diagram)

# 6. Anomaly Detection
def detect_anomalies(real_time_data):
    # ... (Implementation using suitable anomaly detection algorithms)

# 7. API for Model Deployment (Example using Flask)
from flask import Flask, request, jsonify
app = Flask(__name__)

@app.route('/predict', methods=['POST'])
def predict():
    data = request.get_json()
    prediction = model.predict(data)
    return jsonify(prediction.tolist())
```

IA Générative | Generative AI

- L'IA générative est un sous-ensemble du deep learning, ce qui signifie qu'elle utilise des réseaux de neurones artificiels et peut traiter des données étiquetées et non étiquetées.
- L'IA générative apprend la structure sous-jacente des données et peut ensuite générer de nouveaux échantillons similaires aux données sur lesquelles elle a été entraînée.

What is Generative AI?

- AI that creates original content: text, images, code, even 3D models.
- Goes beyond prediction – it generates novel and useful outputs.



Generative AI: A Paradigm Shift

Why It Matters for Oil & Gas:

- Unprecedented ability to model complex geological formations and scenarios.
- Potential to accelerate innovation, reduce costs, and improve safety and efficiency across the value chain.
- Aligns with the Sonatrach's strategic goals of promoting technological advancements and sustainable development in the gas industry.

l'IA générative peut aider Sonatrach à:

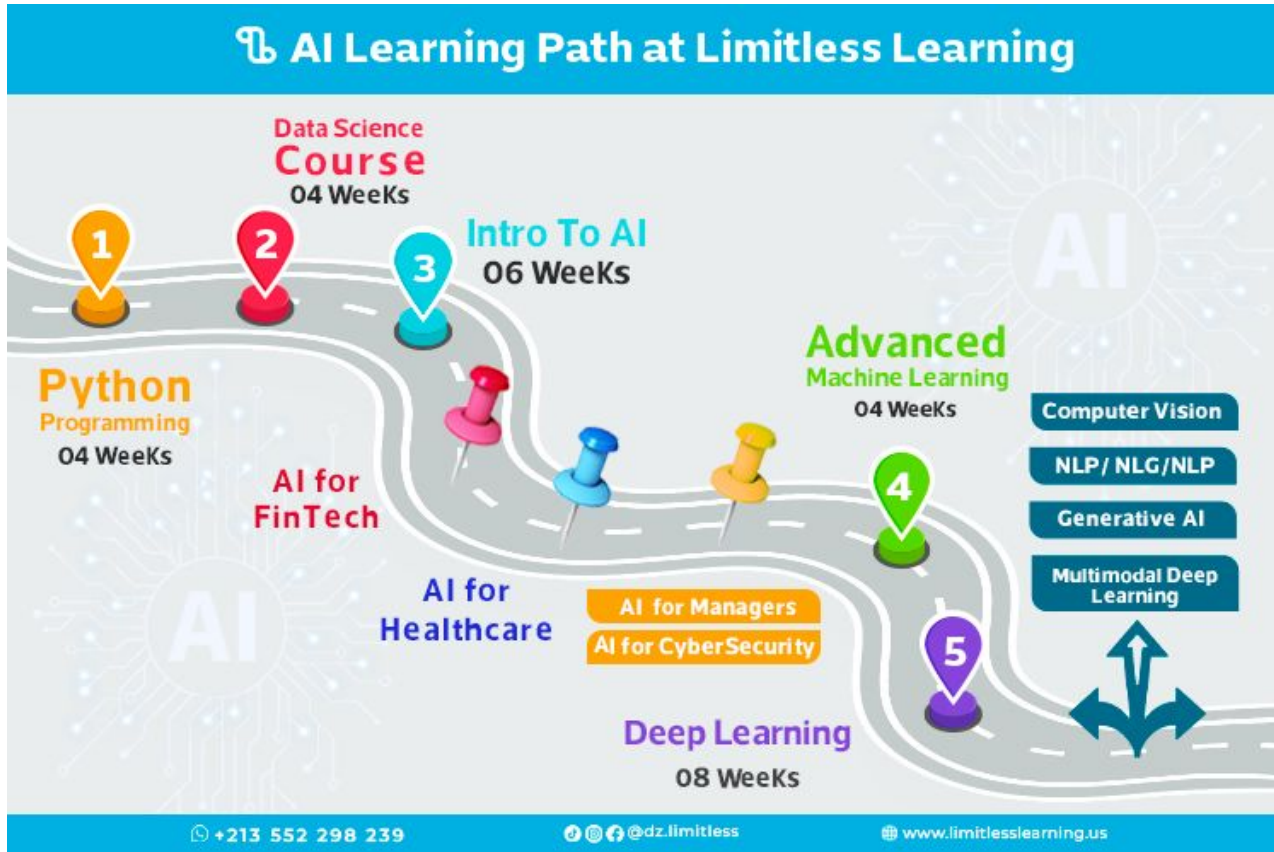
- Améliorer l'efficacité opérationnelle
- Réduire les coûts
- Améliorer la sécurité
- Stimuler l'innovation
- Réduire l'impact environnemental

سوناطراك



sonatrach

Training with **LimitlessLearning.US**



Transforming Exploration with Generative AI

Seismic Data Generation:

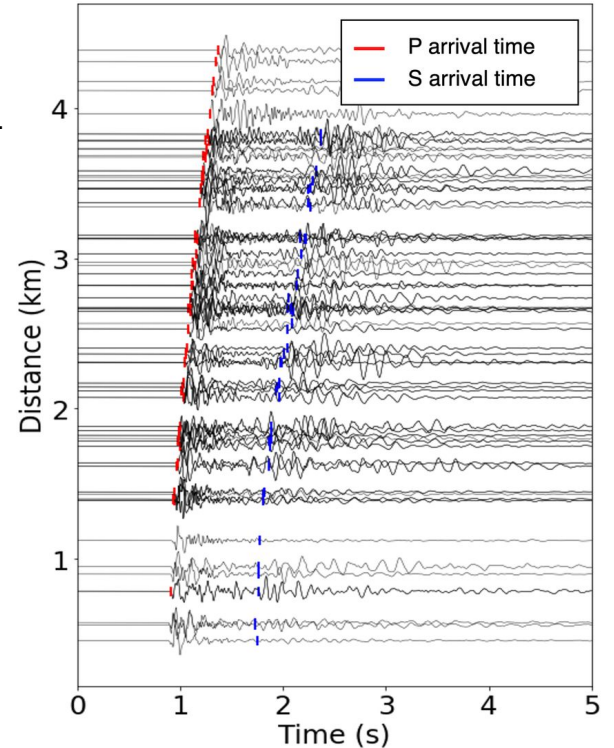
- Generate synthetic seismic data to augment real-world data for training algorithms.
- Enhance subsurface imaging and interpretation, leading to more accurate resource assessments.

Reservoir Modeling:

- Create realistic reservoir models with greater flexibility and fewer uncertainties.
- Optimize production planning, well placement, and resource allocation.

Scenario Simulation:

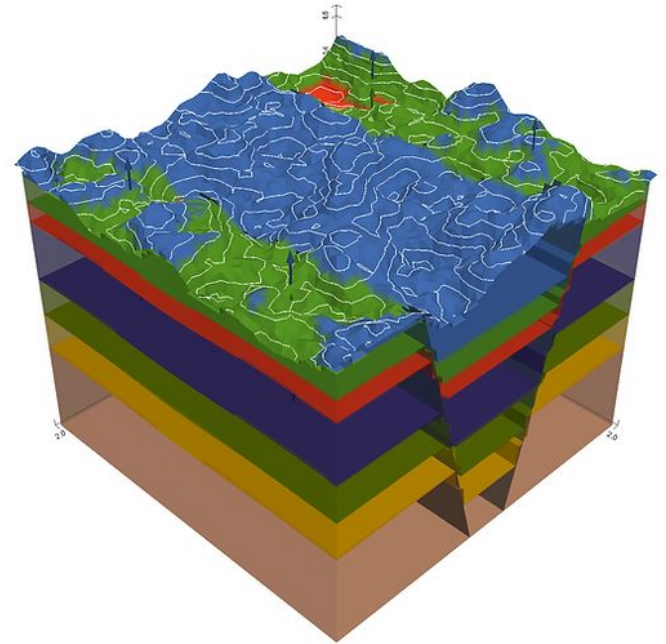
- Simulate potential drilling outcomes under various geological conditions.
- Assess risks, optimize drilling strategies, and reduce the likelihood of costly dry wells.



Generating Synthetic Seismic Data

Workflow Example:

1. **Build a Realistic Model:** Construct a 3D geological model of the subsurface incorporating known geological features and properties.
2. **Simulate Seismic Data:** Generate synthetic seismic gathers based on the model using a seismic modeling software.
3. **Add Realistic Noise:** Incorporate random noise and other real-world artifacts into the synthetic data to make it resemble real seismic data.
4. **Train Algorithms:** Use the augmented dataset (real + synthetic) to train machine learning algorithms for tasks like fault detection, horizon tracking, or reservoir characterization.
5. **Validate and Refine:** Evaluate the trained algorithms on new real-world data to ensure their performance and refine them as needed.



Build a Realistic Model

Dataset: Well logs (gamma-ray, resistivity, density, etc.) Seismic surveys (if available) Geological maps and cross-sections

Tools: GemPy: An open-source Python library for 3D geological modeling.

```
[ ] import gempy as gp

# Create a gempy project
geo_model = gp.create_model('my_model')

# Load data (well logs, geological interpretations)
# ... (See GemPy documentation for loading data)

# Define geological series, surfaces, and faults
# ...

# Set up the model grid and compute the 3D geological model
gp.set_interpolation_data(geo_model, theano_graph=gp.compute_model(geo_model))

# Visualize the 3D model
gp.plot_3d(geo_model)
```

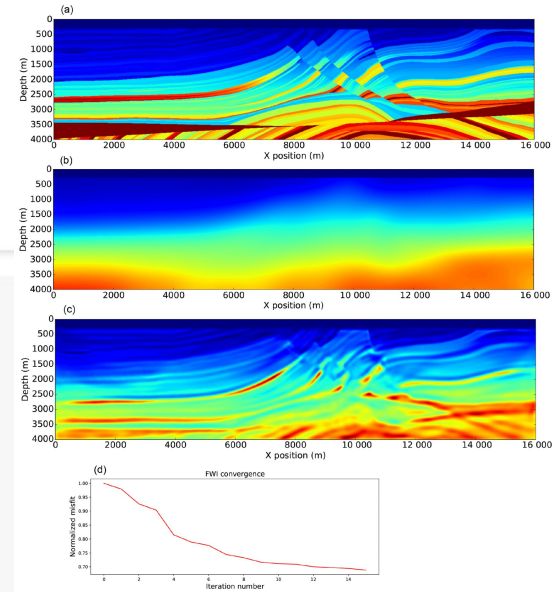
2. Simulate Seismic Data

Tools: Devito: An open-source finite-difference seismic modeling library.

```
[ ] from devito import configuration
configuration['log-level'] = 'WARNING'
import numpy as np
import devito as dv
from examples.seismic import demo_model, AcquisitionGeometry

# Define model parameters (based on your geological model)
shape = (101, 101) # Number of grid points in x and z directions
spacing = (10., 10.) # Grid spacing in meters
origin = (0., 0.) # Origin of the computational domain

# Create the model
model = demo_model('layers-elastic', origin=origin, shape=shape, spacing=spacing,
                  nbl=40, space_order=2, nlayers=2)
```



3. Add Realistic Noise



Tools: NumPy: For numerical operations and random number generation.

```
[ ] import numpy as np

# Get the simulated seismic data (replace with your actual data)
seismic_data = ...

# Add random noise (Gaussian or other types)
noise_level = 0.1 # Adjust as needed
noise = np.random.normal(0, noise_level, seismic_data.shape)
noisy_seismic_data = seismic_data + noise
```

4. Train Algorithms

✓ 4. Train Algorithms

Tools: Scikit-learn: For machine learning algorithms.

TensorFlow/Keras: For deep learning.



```
▶ from sklearn.model_selection import train_test_split
  from sklearn.ensemble import RandomForestClassifier

  # Prepare your data (features and labels)
  X = ... # Features (e.g., attributes extracted from seismic data)
  y = ... # Labels (e.g., fault/no fault, horizon depth)

  # Split into training and testing sets
  X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2)

  # Train a classifier
  clf = RandomForestClassifier()
  clf.fit(X_train, y_train)
```

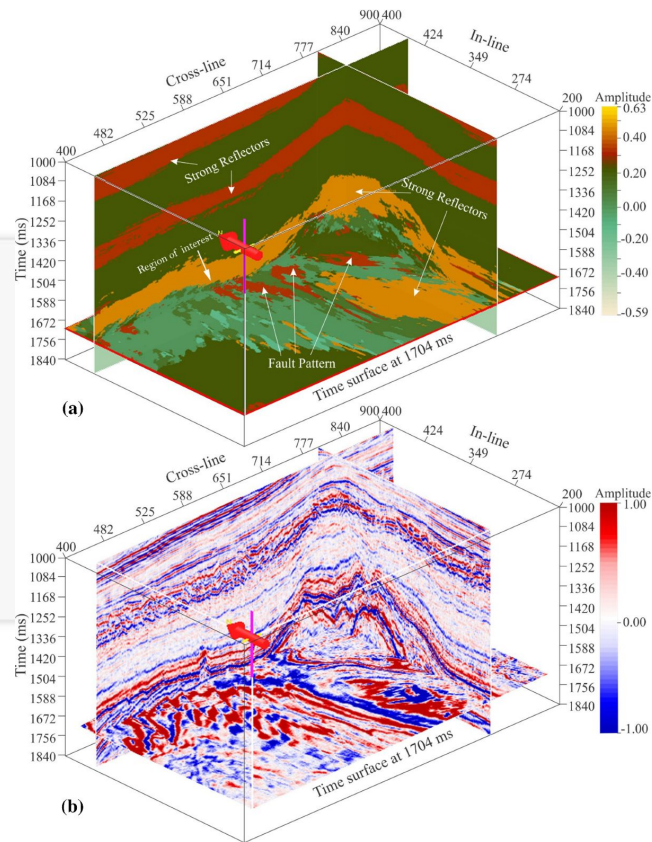


5. Validate and Refine



```
# Evaluate on the test set  
y_pred = clf.predict(X_test)  
accuracy = np.mean(y_pred == y_test)
```

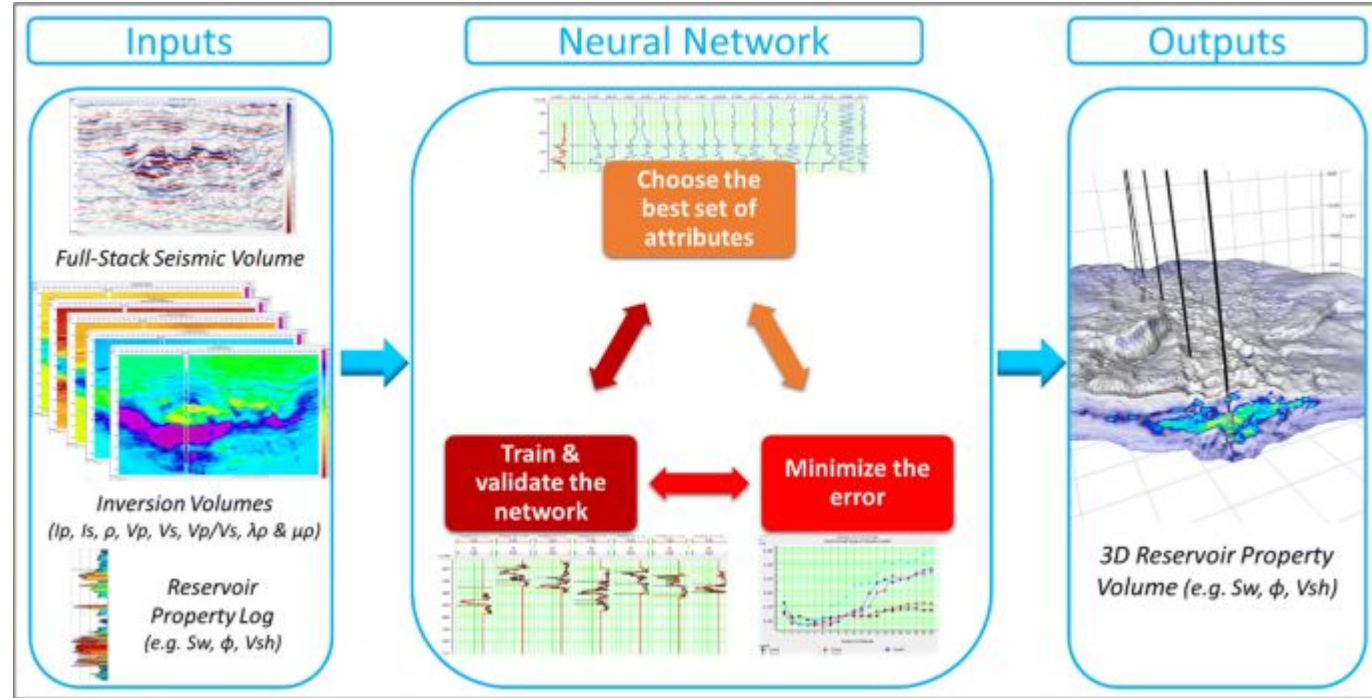
```
# Refine the model:  
# - Try different algorithms  
# - Adjust hyperparameters  
# - Add more features
```




Result


Trained machine learning model that can analyze real-world seismic data to detect faults, track horizons, or characterize reservoirs.



The model's performance is validated on unseen data, giving you confidence in its accuracy and reliability.




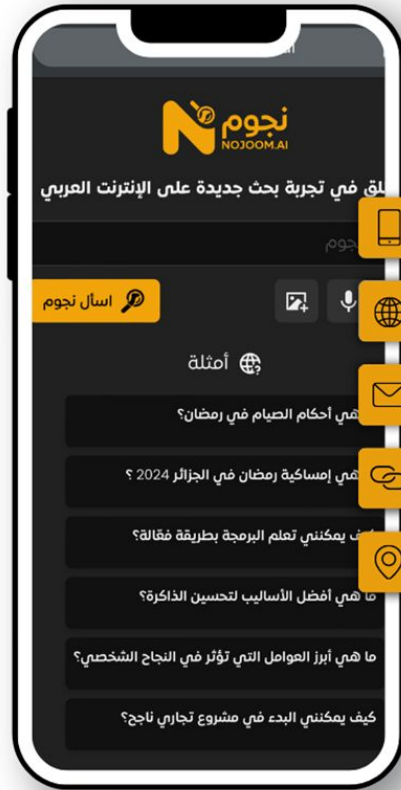
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Backup

The process of creating a Reservoir modeling AI workflow using synthetic data

1. Dataset Creation

Real Data: Gather well logs (gamma-ray, resistivity, etc.), core samples, seismic data (if available), and any other relevant geological data from your reservoir area.

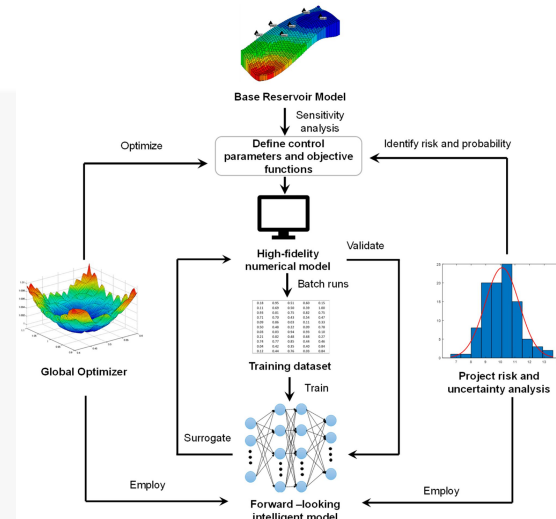
Synthetic Data Generation:

```
[ ] import numpy as np
import geostatspy.GSLIB as GSLIB
import geostatspy.geostats as geostats

# Load real data (example with well logs)
well_data = pd.read_csv("well_logs.csv")

# Generate synthetic property distributions (example with porosity)
porosity_model = GSLIB.sgsim(100, 100, 1, seed=123)

# Combine real and synthetic data (if needed)
augmented_data = pd.concat([well_data, pd.DataFrame(porosity_model)], axis=1)
```



2. Feature Engineering

Extract Features: The dataset, derive relevant features for reservoir modeling.

This could include:

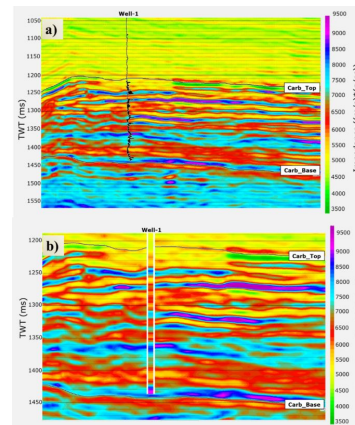
- Petrophysical properties (porosity, permeability)
- Structural features (fault proximity, dip angle)
- Seismic attributes (amplitude, frequency)

Data Preprocessing:

- Normalize, standardize, or clean your data to ensure it's suitable for machine learning algorithms.

```
[ ] from sklearn.preprocessing import StandardScaler

# Standardize features
scaler = StandardScaler()
scaled_data = scaler.fit_transform(augmented_data)
```



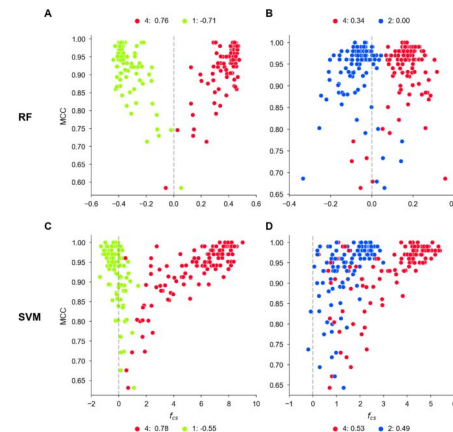
3. AI Model Selection and Training

Choose Algorithm:

- Select a machine learning algorithm appropriate for your task.

Some common choices include:

- **Random Forests:** For regression tasks (e.g., predicting porosity values)
- **Support Vector Machines (SVM):** For classification tasks (e.g., identifying lithofacies)
- **Neural Networks:** For complex relationships or when integrating seismic data



```
[ ] from sklearn.ensemble import RandomForestRegressor

# Split data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(scaled_data[:, :-1], scaled_data[:, -1], test_size=0.2)

# Train model
model = RandomForestRegressor(n_estimators=100)
model.fit(X_train, y_train)
```

4. Model Evaluation

Assess Performance:

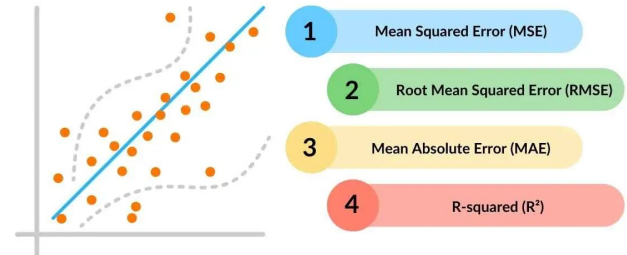
- Evaluate your model's accuracy using metrics appropriate for your task (e.g., mean squared error for regression, accuracy for classification).

Validation: Validate your model on a separate dataset to ensure it generalizes well to new, unseen data.

```
[ ] from sklearn.metrics import mean_squared_error

# Predict and evaluate on test set
y_pred = model.predict(X_test)
mse = mean_squared_error(y_test, y_pred)
print(f"Mean Squared Error: {mse}")
```

4 Common Regression Metrics



5. Model Application

Reservoir Modeling: Use your trained AI model to predict reservoir properties in areas where data is sparse. Optimize

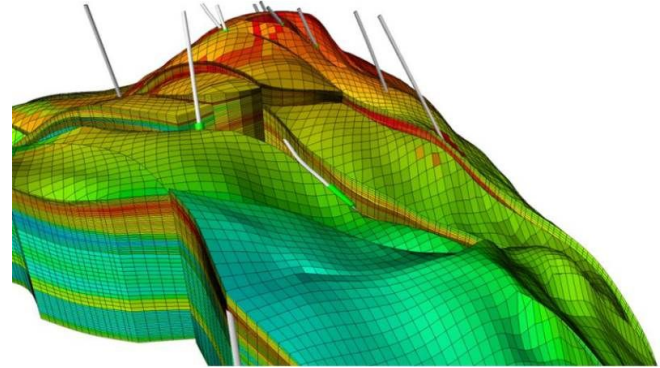
Production: Integrate your model into reservoir simulation software to optimize well placement, production rates, and recovery strategies.

Example Result:

- You've built an AI model that can accurately predict porosity distribution across your reservoir. This model is now a valuable tool for guiding decision-making, reducing uncertainty, and improving overall reservoir management.

Key Points:

- Synthetic data is crucial for expanding your dataset and covering geological scenarios not present in real data. Feature engineering is key to extracting meaningful information from your data.
- Choose the right AI algorithm based on the task and nature of your data. Thoroughly evaluate and validate your model to ensure its reliability.



Revolutionizing Operations with Generative AI

Predictive Maintenance:

- Generate synthetic sensor data to train predictive maintenance models.
- Proactively identify equipment anomalies and potential failures, enabling timely interventions.

Optimization of Production Processes:

- Design novel chemical formulations for enhanced gas recovery.
- Optimize drilling parameters in real-time based on dynamic subsurface conditions.

Supply Chain Optimization:

- Generate scenarios for supply chain disruptions and optimize logistics.
- Improve resource allocation, reduce operational costs, and enhance resilience.



Enhancing Decision-Making with Generative AI

Scenario Planning:

- Generate diverse market scenarios to assess potential risks and opportunities in the global gas market.
- Make informed investment and operational decisions based on data-driven insights.

Data Augmentation:

- Synthesize missing or incomplete data to improve the accuracy of AI models used for decision support.
- Enhance decision-making with more comprehensive and reliable information.

Risk Assessment:

- Simulate potential accidents and hazards in gas production and transportation.
- Develop effective safety protocols and mitigation strategies.
- Create virtual training environments for complex and high-risk operations.



Challenges and Considerations

Data Quality and Quantity:

- Generative AI models require large amounts of high-quality, domain-specific data to be effective.
- Collaboration among GECF members to share data can address this challenge.

Interpretability:

- The outputs of generative models can be complex, requiring careful interpretation and validation.
- Building trust in AI-generated insights is crucial for decision-makers.

Ethics and Bias:

- Proactive measures are needed to avoid biases in data and algorithms.
- Ensure responsible and ethical AI use in alignment with GECF principles.



The Future of Generative AI in Oil and Gas

Continued Advancements:

- Expect rapid progress in generative AI capabilities and applications tailored to the oil and gas industry.

Integration with Existing Systems:

- Combining generative AI with traditional simulation and modeling tools will unlock new levels of insight and optimization.

New Business Models:

- Generative AI could enable innovative service delivery models and create new value streams in the gas sector.

