



From Al Foundations to Real-World Practices

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 - Maintenance: Adapt to data drift, optimize cost & performance.

- Key Constraints for Al Products:
 - Data availability, quality and labeling effort.

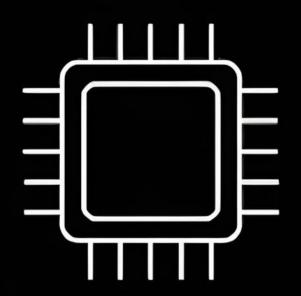
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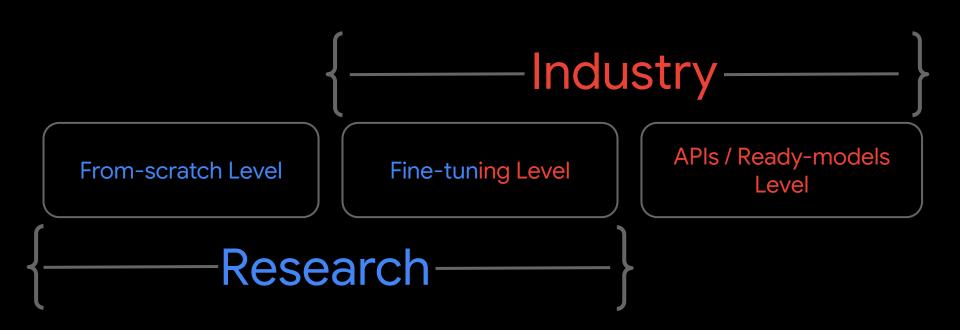
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 - Privacy & Governance Boundaries closed source vs open source solutions.
 - Budget API spend, compute bills, labor & labeling costs.
 - ⇒ Every stage balances these constraints.
 - ⇒ Start as simple as possible, then iterate toward the most efficient long-term solution.



Implementation Levels for AI Solutions



Level	What to do / use?	When to Choose
APIs / Ready-models Level	 Using closed-source APIs (OpenAI, Google Vertex,) Using zero-shot models (LLMs, SAM, Yolo-World,) Using publicly available models from Github / Hugging Face / 	
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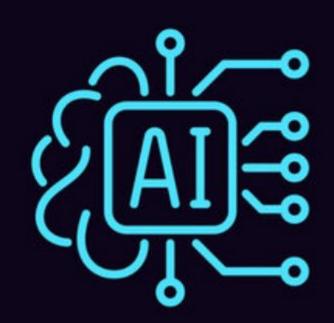
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From-scratch Level	Training from scratch / novel architectures	1- Research novelty.2- Unavailable model.

Open-Source vs Closed-Source

- Prototype fast?
 - ⇒ Whichever gets you a demo quicker, but mostly closed-source.
- Strict data privacy or customisation need?
 - ⇒ Open-source and self-host.
- Need battle-tested uptime & rapid scaling & better performance?
 - ⇒ Closed-source.



You just joined a company and heard:

"We need an AI solution for this problem."

 Which clarifying questions will you ask before writing a single line of code?

- What Problem Are We Solving?
 - ⇒ Immerse in the domain: Let stakeholders explain the issue in their own language; capture pain-points, constraints, success criteria.
 - → Translate to Al language: Re-frame domain terms into ML tasks classification, detection, ranking, forecasting, etc (Kaggle experience helps a lot here).

- Do We Even Need AI to solve this problem?
 - ⇒ Stakeholder and customers wants to through Al on everything.
 - ⇒ There are many problems in real world that don't need Al at all.
 - ⇒ Are you sure you want to use AI to solve a problem?

Or just to introduce some new fancy useless feature?

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But, how to know if a problem is solvable by Al or not?

- 1. Human Baseline: Can humans do this? how well?
- 2. Previous Work: Papers, benchmarks, existing APIs, Kaggle competitions, public repositories.
- 3. Data Reality: Do we have (or can we get) labelled examples?

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Let's see some examples...

Problem: I want to read all car license plate numbers.

⇒ Human Baseline:

⇒ Pipeline:

Problem: I want to read all car license plate numbers.

⇒ Human Baseline: Very easy task, thus Al can do it as well.

⇒ Pipeline: Detection + OCR.

 Problem: I want to predict the weight of an object based on its image.

⇒ Human Baseline:

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- Problem: I want to predict the weight of an object based on its image.
 - ⇒ Human Baseline: Not easy. Probably with medium accuracy.
 - ⇒ Pipeline: Image regression on height, width and depth. Then some math to convert to weight.

 Problem: I want to predict the price of a house based on its color.

⇒ Human Baseline:

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 Problem: I want to predict the price of a house based on its color.

⇒ Human Baseline: impossible. There is no predictive signal in color.

 Problem: I want to predict whether a user will like a specific phone.

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- Problem: I want to predict whether a user will like a specific phone.
 - ⇒ Human Baseline: Possible. I just need the user history.
 - ⇒ Pipeline: Recommendation system task.

 Problem: I want to build a model that translates cat meows into human language.

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 Problem: I want to build a model that translates cat meows into human language.

⇒ Human Baseline: Impossible. No ground truth.

 Problem: I want to forecast my company's sales 10 years into the future.

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 Problem: I want to forecast my company's sales 10 years into the future.

⇒ Human Baseline: Extremely difficult with good accuracy.Long-term forecasting is unstable.

⇒ Pipeline: Time series forecasting.

 Problem: I want to help blind people know if there's something near them.

⇒ Human Baseline:

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- Problem: I want to help blind people know if there's something near them.
 - ⇒ Human Baseline: Possible. But I see many object in the street, which one should i describe?
 - ⇒ Pipeline: Detect → Classify (needs many classes or zero-shot capabilities) → Text-to-speech.
 - ⇒ Challenges: real-time processing, model size, speech quality.

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- Problem: I have characteristics of all my store branches and want to understand what makes each one special.
 - ⇒ Human Baseline: Possible. I can look into each store data and cluster them accordingly.
 - ⇒ Pipeline: Clustering, or classification on store IDs, then analyze feature importance.

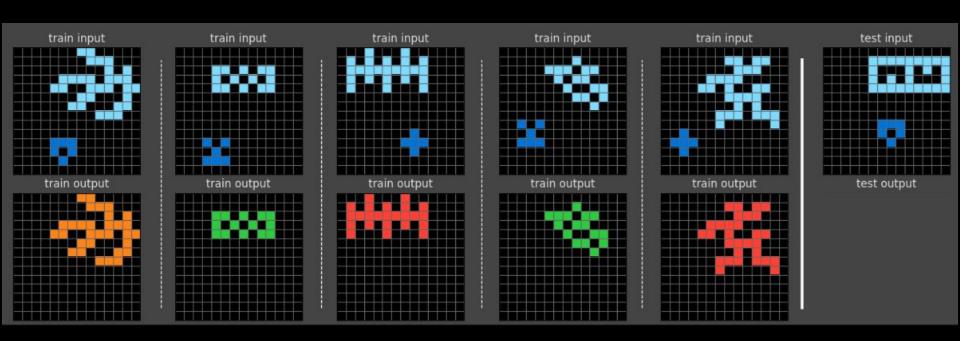
Problem: I want to predict if my tweet will go viral.

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- Problem: I want to predict if my tweet will go viral.
 - ⇒ Human Baseline: Maybe. Likely low accuracy.
 - ⇒ Pipeline: Text classification (define what "viral" means first!)

Problem: I want AI to solve this puzzle:



- Problem: I want AI to solve this puzzle:
 - ⇒ Human Baseline: Very easy.
 - ⇒ Al Solution: Extremely difficult!!!!!!
- This puzzle is part of a famous benchmark called ARC-AGI. All puzzles in this benchmark are easily solvable by humans, but so far, no Al has been able to solve them! <u>link</u>

Let's get back to scoping Al problems...

Data?

- What types of data do I need? And how much do I need to build a reliable system? ⇒ depends on the task and the availability of pretrained models.
- Is it available? No? ⇒ Can i collect it? No? ⇒
 Can I generate it? No? ⇒ Can I just use a zero-shot model to do the task?
- Is the data quality good enough for a good model?
- Unlabeled data? ⇒ Manual or Automatic Labeling.
- Is the data private? No? ⇒ I can use closed-source.

- What resources will be used for inference?
 - I can use GPU? ⇒ All types of solutions.
 - CPU only? ⇒ APIs + Non-DL solutions + small DL solutions (efficient and mobile architectures).
 - Edge Device? ⇒ APIs + Non-DL solutions + Extremely small DL solutions (should fit in small memory, e.g. < 64 MB).

- Real-time or not?
 - Yes? ⇒ Hard problem.
 - You should decrease your models size as small as possible.
 - You should increase your inference resources as high as possible.
 - You should rely less on APIs, because of latency (it depends).
 - No? ⇒ :)

- Any existing solutions?
 - Yes? ⇒ Understand it thoroughly. Consider as a baseline. Start from there.
 - No? ⇒ Search in the internet.

- How to Think of Useful Features / Modeling ideas for this particular task?
 - Consider how a human would approach and solve the task.
 - Ask yourself: What information would I rely on to make an accurate decision in this context?
 - Translate that intuition into features.
 - Insights derived from human judgment often map directly to meaningful input variables.

- How to evaluate the model?
 - Real data exist?

 - No? Can I collect? No? Can I generate synthetic data that mimics my real world scenario?
 - <u>Fine-tuning / From-Scratch:</u> train on real / synthetic data, evaluate on real data.
 - APIs: no training, evaluate on real data.

- What metric should I use?
 - Depends on the task (Regression, classification, retrieval,...).
 - Within each task, there are special metrics (e.g. MAE, RMSE, MAPE, SMAPE,...).
 - Each one serves a specific use case (e.g. I care about relative distance more than raw distance, MAE vs MAPE).
 - For more: <u>link</u>

• Ok, now we collected accurate information about the project. Let's craft a solution...

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 - a. Closed-source? ⇒ start replacing each closed-source component with an open-source one, and inspect performance difference.
 - b. Resources intensive? Optimize the models sizes / input / preprocessing / GPUs-CPUs utilization.
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- 3. Perfect? ⇒ Deploy on small scale!
- 4. Perfect? ⇒ Deploy on a large scale, and monitor!

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 - d. \times "The tone is too harsh for young learners." \Rightarrow Fine-tune TTS or find a better one.
 - e. X "Someone hacked the prompt!" → Add prompt-guarding, filtering, and robustness checks.
- 3. When it's stable:
 - a. Deploy small-scale \rightarrow Collect feedback \rightarrow Iterate.
 - b. Then deploy large-scale with monitoring, and keep improving.

Deployment Patterns

- Ready-made API (OpenAI, AWS Rekognition, etc.)
 - a. Model is hosted by the provider.
 - b. No need to worry about scalability or infrastructure.
- 2. Self-hosted API (Flask / FastAPI in Docker)
 - a. Custom model, hosted on your own server and exposed as an API.
 - b. Full control you must handle infrastructure, uptime, and scaling.
- 3. Edge / On-device (ONNX, TFLite, CoreML):
 - a. Custom model runs directly on the target device.
 - b. Zero network latency & strong privacy.
 - c. Common in IoT and mobile deployments.

Note: Learn about cloud tools (e.g. AWS, GCP, etc.) — they're essential in real-world deployments.





Thanks for Attending!

Prepared by: Mohamed Eltayeb