

AI Productization: Models and Beyond

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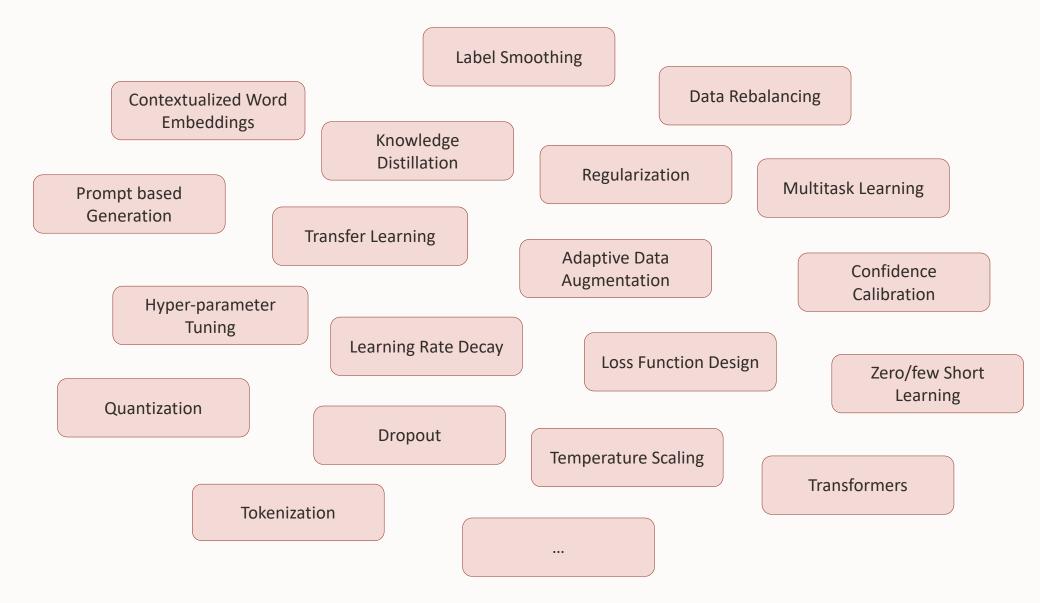


Davis Hong











Text Classification Classification **Sentiment Analysis Data Rebalancing** Models **Language Detection** Tokenization Named Entity Recognition & Linking Sequence Contextualized Word Aspect-Oriented Sentiment Labeling Embeddings Analysis Models **Key Phrase Extraction Transfer Learning** Forms Recognition **Semantic Parsing** Hyper-parameter Tuning **Machine Translation** Seq2seq Models **Text Normalization Adaptive Data** Natural Language Augmentation Generation Confidence **Topic Models** Calibration Clustering **Out-of-domain Detection** Models **Dialog Clustering**

Conversation

Dialog Management API Channel Extension API Domain Classification API Transcript Analysis API

Language

Text Classification API Entity Recognition API Key Phrase Extraction API Sentiment Analysis API

Speech

Speech Recognition API Video Transcription API Speech Id & Diarization API Speech Synthesis API

Documents

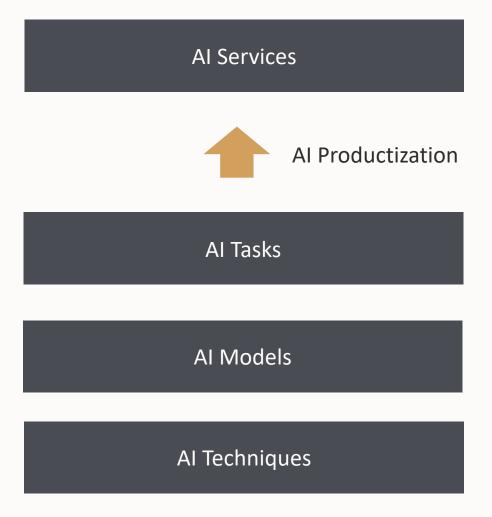
Document Analysis API Document Extraction API Document Verification API

Translation

Language Detection API Neural Machine-- Translation API

DEMO





Overview

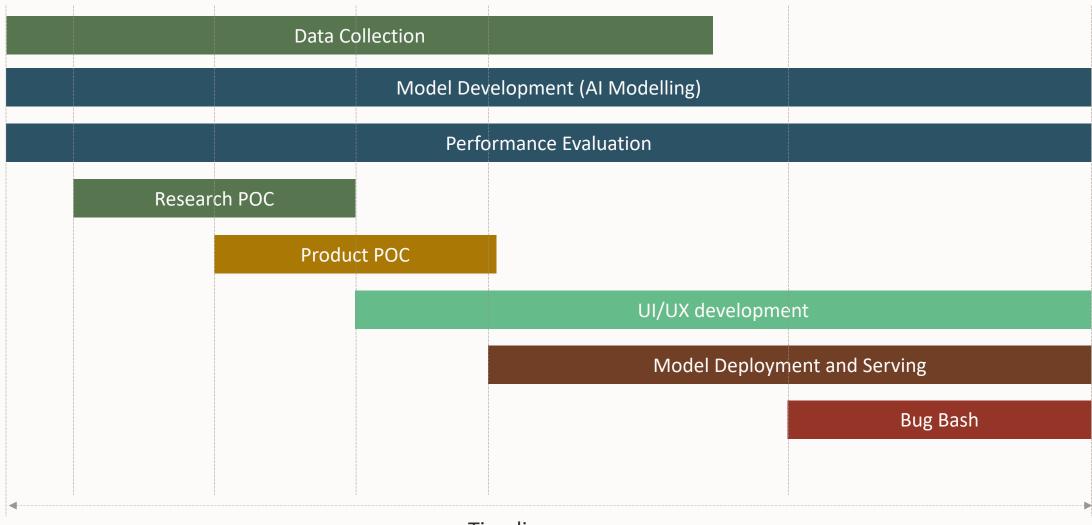
What is AI Productization?

- NLP Techniques
- Models and Tasks
- Services in Production

Beyond AI Modellings

- Running an Al project
- Discussion: Data Collection
- Discussion: Deterministic and Stable Training
- Discussion: Performance Latency Trade-off









Beyond AI Modellings: Data Collection

Public Data

Customer Data

From 3rd Party

Data Collection

Model Development (AI Modelling)

Public Data

- License checking → <u>Legal Approve</u>
- This determines whether the dataset can be used for different purposes, e.g. benchmarking/evaluation, hyperparameter tuning, production, etc.

Customer Data

- Highly confidential
- It may involve PII/PHI application → PII /PHI removal



Beyond AI Modellings: Data Collection

Public Data

Customer Data

From 3rd Party

Data Collection

Data Collection From 3rd Party

- Data Collection Guidelines
 - Definition of the Task; Example Annotations; Borderline Use Cases; Annotation Rules;

Model Development (Al Modelling)

- Evaluation Metrics; Estimated Target Performance
- Quality Control
 - Pilot Run and Production Batches
 - Annotation Auditing
 - Data Quality Evaluation
 - Feedback List Curation
 - Annotator Performance Evaluation



Model Development (AI Modelling) Literature Review Model Research and Development Hyper-parameter Tuning

For **Literature Review**, we collect recent research papers that are relevant to the target task, compile them into a list, share with the team, and call for discussion.

For **Model Research and Development**, we aim at

- recover the performance reported in the paper; then
- customize the model for our specific tasks; and
- if the model achieves promising performance, we will incorporate it into our internal ML/DL framework:
 OPALS



Model Development (AI Modelling)

Literature Review

Model Research and Development

Hyper-parameter Tuning

Hyper-parameter tuning is used to select the pretrained contextualized embeddings and plausible hyper-parameter combinations.

- In real application, hyperparameters could be tuned based on <u>large number of evaluation sets</u>, e.g. thousands of evaluation sets. → <u>Multi-objective optimization</u>
- Hyperparameter tuning with customization:
 - Imposes training and runtime resource constraints, e.g. time, memory, etc
 - Prefers hyper-parameters that provide training stability
 - Ignores unstable data points
- Auto-ML style functionality automatically suggests hyperparameters according to data shapes.



Model Development (AI Modelling)								
Performance Evaluation								
Competitor Benchmarking	Customer Regression	Evaluation Tool						

Competitor Profiling

- Competitor Profiling involves service feature and function comparison.
- For example, with text classification, some competitors may provide Out-of-Domain Detection, some may provide multi-label classification, some may provide support for more languages, etc.

Competitor Benchmarking

- For AI models, we care about
 - Model performance based on metrics such as accuracy, F1, AUC, etc. depending on the task
 - Training/Inference latency
 - How <u>easy</u> it is for developers/users to use



Model Development (AI Modelling)

Performance Evaluation

Competitor Benchmarking

Customer Regression

Evaluation Tool

Customer Regression

- Performance maintenance over releases
 - Macro regression: drop of performance in percentage, e.g. on accuracy
 - Micro regression: drop of performance on specific test examples
- Model determinism and stable training
 - Model determinism: deterministic training across N training runs
 - Stable training: across N training runs, different computing shapes, dependency package upgrades, model updates, etc
- Customer regression minimization and Hyperparameter tuning strategies
 - Penalizes regression more than reward improvements



Model Development (AI Modelling)								
Performance Evaluation								
Competitor Benchmarking	Customer Regression	Evaluation Tool						

Evaluation Tool

- Different Test Types that are representative of <u>different model features</u>, e.g. class imbalance, out-of-domain (OOD) detection, multi-label classification, overfitting issue, etc.
- Different Test Types that are reflective of <u>different behavioral tests</u>, e.g. robustness, temporal, negation, etc.
- Delta columns that show the <u>performance regressions</u> between model releases.
- Status columns that indicate whether the test on a dataset is a PASS or FAIL: <u>acceptance rate</u>.
- Each individual regressed example should be tracible for <u>manual investigation</u>.
- Results from internal <u>model explainability tools</u> to help manual investigation.



Behavioral Testing

Negation	<i>MFT:</i> Negated negative should be positive or neutral	18.8	54.2	29.4	13.2	2.6	The food is not poor. pos or neutral It isn't a lousy customer service. pos or neutral
	<i>MFT:</i> Negated neutral should still be neutral	40.4	39.6	74.2	98.4	95.4	This aircraft is not private. neutral This is not an international flight. neutral
	MFT: Negation of negative at the end, should be pos. or neut.	100.0	90.4	100.0	84.8	7.2	I thought the plane would be awful, but it wasn't. pos or neutral I thought I would dislike that plane, but I didn't. pos or neutral
	MFT: Negated positive with neutral content in the middle	98.4	100.0	100.0	74.0	30.2	I wouldn't say, given it's a Tuesday, that this pilot was great. neg I don't think, given my history with airplanes, that this is an amazing staff. neg
NER	INV: Switching locations should not change predictions	7.0	20.8	14.8	7.6	6.4	@JetBlue I want you guys to be the first to fly to # Cuba → Canada INV @VirginAmerica I miss the #nerdbird in San Jose → Denver INV
	<i>INV:</i> Switching person names should not change predictions	2.4	15.1	9.1	6.6	2.4	Airport agents were horrendous. Sharon → Erin was your saviour INV @united 8602947, Jon → Sean at http://t.co/58tuTgli0D, thanks. INV
Robust.	INV: Add randomly generated URLs and handles to tweets	9.6	13.4	24.8	11.4	7.4	@JetBlue that selfie was extreme. @pi9QDK INV @united stuck because staff took a break? Not happy 1K https://t.co/PWK1jb INV
	<i>INV:</i> Swap one character with its neighbor (typo)	5.6	10.2	10.4	5.2	3.8	@JetBlue → @JeBtlue I cri INV @SouthwestAir no thanks → thakns INV

Examples from "Beyond Accuracy: Behavioral Testing of NLP Models with CheckList, ACL 2020"



Beyond AI Modellings: Model Prototyping and Service Demo

Model Development (AI Modelling)

Research POC

Product POC

Research POC (proof-of-concept)

- To prove that an AI service is theoretically and empirically possible
- It involves public data collection; model prototyping; performance evaluation; and comparison with SOTA performance in research papers on public benchmarks.

Product POC

- To provide a service demo that shows the main functions and features of an AI service
- It involves use case or feature planning, UI/UX development, competitor profiling, and <u>potential</u> <u>customer identification</u>
- In this stage, we can start designing input and output APIs, e.g. what is expected from the end user, and what will be responded to them.





Model Research and Development (AI Modelling)

Model Deployment and Serving

Bug Bash

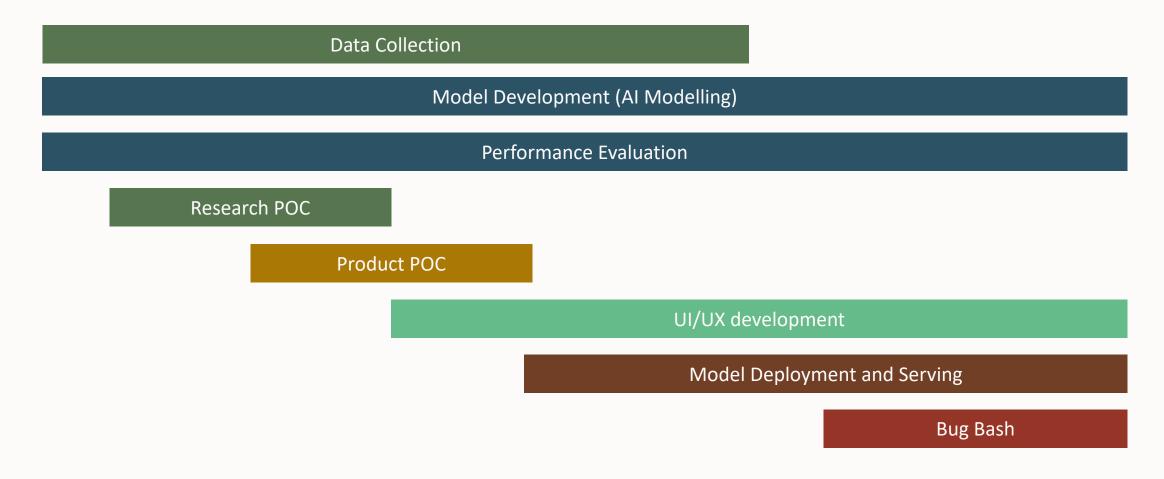
Model Deployment and Serving

- Running machine learning model in Docker
- Deploying model based on different DL libraries, e.g. TensorFlow, PyTorch, etc.
- Loading test: to test how the model is coping with N requests per second (RPS)
- Resource sharing: embedding as a service, caching mechanism, language detection, etc.

Bug Bash

- Internal or cross-team bug bash
- Pre-production bug bash helps identify bugs that could appear at all corners
 - unexpected model output, e.g. a model could give weird output for gibberish inputs
 - latency issues, e.g. a response takes longer than expected to complete
 - UI/UX bugs, e.g. not responsive to a button





Innovation is encouraged in every stage of this pipeline.

- Our team filed **58 patents** in the last 3 years
- We encourage team members to attend AI/NLP/CV conferences and forums
- We encourage literature reviews and blog style discussions



Discussion: Data collection

Text Classification

We want to build a text classifier that classifies text documents to 1000 pre-defined classes identified from prioritized domains. We don't have training examples for building this model; and would like to collect data from 3rd party data collection companies.

- There are hierarchical relations between the 1000 classes.
- One document can be assigned to more than 1 label.
- We can collaborate with multiple 3rd party companies.

How would you run the data collection project?

How can you guarantee the high quality of the collected data?

How would you cope with subjectiveness of the annotation?





Discussion: Data collection

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How would you cope with subjectiveness of the annotation?

As a follow-up, we also want to collect data in Arabic. How would you deal with it?





Discussion: Deterministic and stable training

Regression Analysis

We have a test dataset with 20 test examples from a customer that are considered very important (It could be that our customer uses these 20 examples as demo cases to show to their customers). However, 5 of the previously PASSED test examples FAILED in the recent model update release.

- The model update is the only source of change; nothing in the pipeline around the model has changed; no data change.
- The model update seems not relevant to the 20 test examples. For example, the model update should be only affecting datasets with 10K training examples; while this customer only provided 5K training examples.
- The model is based on adapting a pretrained language model. It involves updating the embedding layers, encoder layers, and the task-specific layers.
- The model is trained on both original data and augmented data. A number of augmentation techniques are applied.
- The model is build based on TensorFlow.

How would you investigate these failed cases and provide an explanation to the customer?





Discussion: Performance - Latency trade-off

Model Inference Latency

We want to release a service; and the project is in the deployment and serving stage. However, we found that the model is responding super slow when it is served for deployment; and the PM is expecting the model to give response in 1/5 of the time.

- The service takes plain text documents as input; and output analytic information about the input documents.
- The current model is based on adapting a pretrained language model. Training the model involves updating the embedding layers, encoder layers, and the task-specific layers.
- The current model is implemented in TensorFlow; and served with TF-Serving.

How would you investigate this problem and provide solution?





We are hiring!

- 1. Our open positions
 - AI/NLP/CV Scientist
 - AI/NLP/CV Engineer
 - AI/NLP/CV Interns (coming soon)
 - Language Engineer (coming soon)

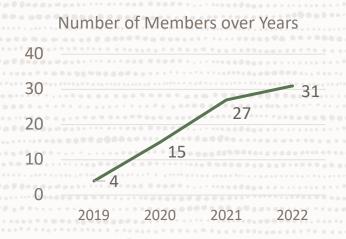
- 2. Our daily work
 - Start-up style
 - Challenging problems and tasks
 - Research-backed product development

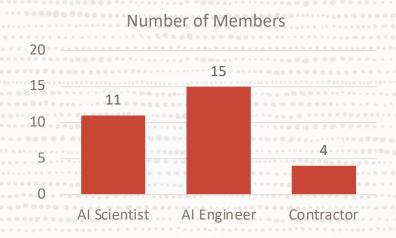
3. OCI Values

- PUT CUSTOMERS FIRST
- ACT NOW, ITERATE
- NAIL THE BASICS
- EXPECT AND EMBRACE CHANGE
- TAKE RISKS, REMAIN CALM
- INNOVATE TOGETHER
- OWN WITHOUT EGO
- EARN TRUST, GIVE TRUST
- TAKE PRIDE IN YOUR WORK
- CHALLENGE IDEAS, CHAMPION EXECUTION



About Our Team





94%

ODA Revenue YoY Growth from FY21 to FY22







~80M

Requests to OCI Language services in FY22



Thank you!



ORACLE

Our mission is to help people see data in new ways, discover insights, unlock endless possibilities.