The Rat Race to Deploy AI Models: The Problem of Being on Top of the Gartner Hype Cycle

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CS846 Course Project

Agenda

Source: http://youberelentless.com/the-top-quotes-about-escaping-the-rat-race/

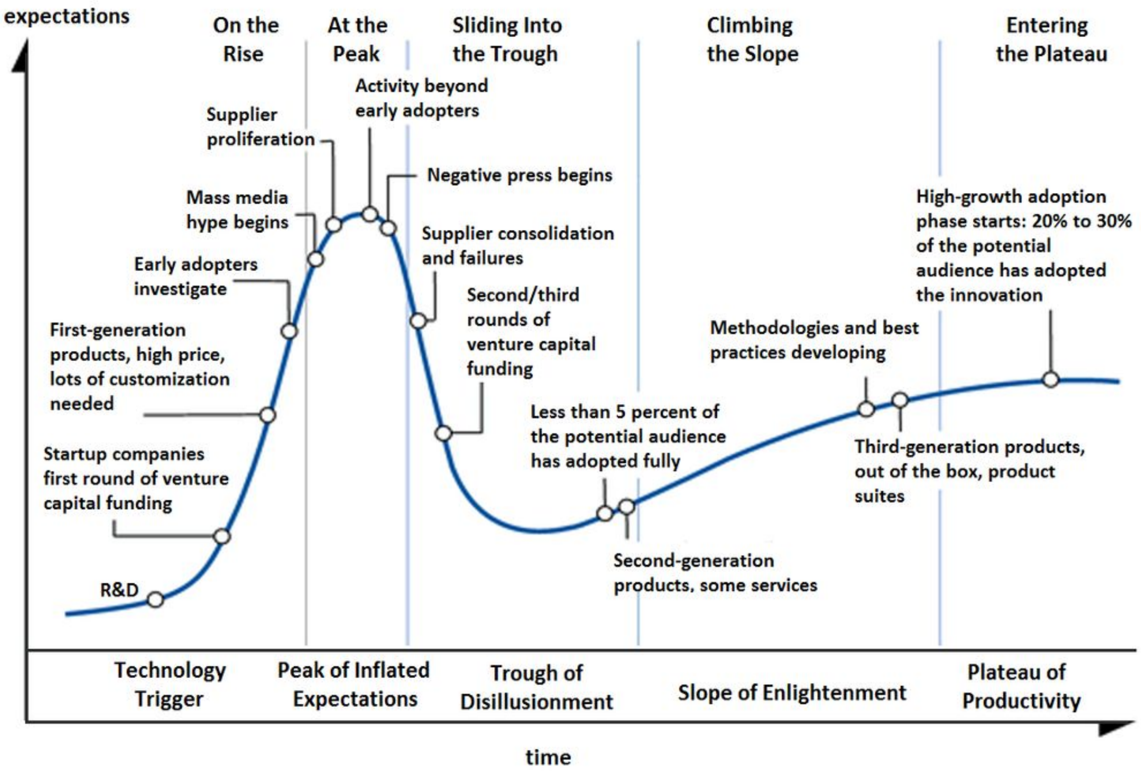
1. Introduction to SDLC
2. GHC and Effects on SDLC
3. Basic Concepts
4. Case Study
5. Post Mortem/Take Aways
6. Conclusion

10 Phases of SDLC:

The Rosy Picture

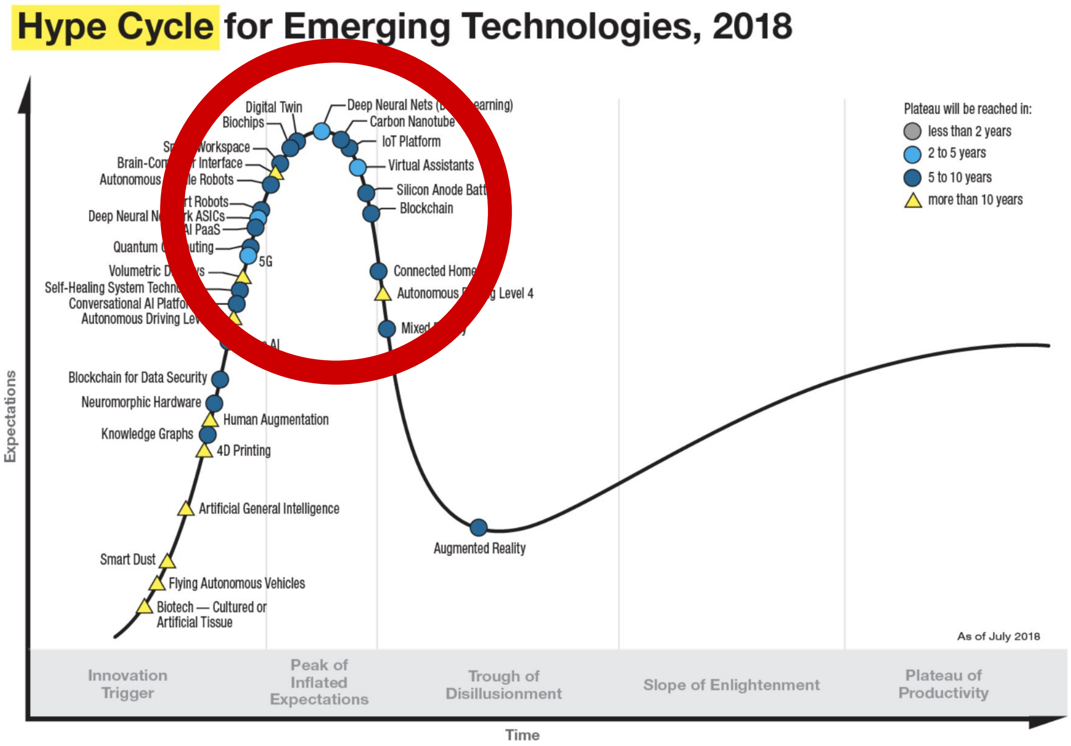
1. Initiation: Identification of Opportunity
2. System Concept Development: Scope & Boundaries of Concept
3. Planning to Acquire Resources
4. Requirements Analysis
5. Design: The How Part
6. Development: Design->System
7. Integration & Testing
8. Implementation: Lab-> Production
9. Operation & Maintenance
10. Disposal : End of Life

Gartner Hype Cycle


expectations
On the Rise
At the Peak
Sliding Into the Trough
Climbing the Slope
Entering the Plateau
Activity beyond early adopters
Supplier proliferation
Negative press begins
Mass media hype begins
Supplier consolidation and failures
Early adopters investigate
Second/third rounds of venture capital funding
First-generation products, high price, lots of customization needed
Methodologies and best practices developing
High-growth adoption phase starts: 20% to 30% of the potential audience has adopted the innovation
Less than 5 percent of the potential audience has adopted fully
Startup companies first round of venture capital funding
Third-generation products, out of the box, product suites
Second-generation products, some services
R&D
Technology Trigger
Peak of Inflated Expectations
Trough of Disillusionment
Slope of Enlightenment
Plateau of Productivity
time

Source: Wikipedia & https://smithhousedesign.com/models-predicting-future-gartners-hype-cycle/

Gartner Hype Cycle 2018

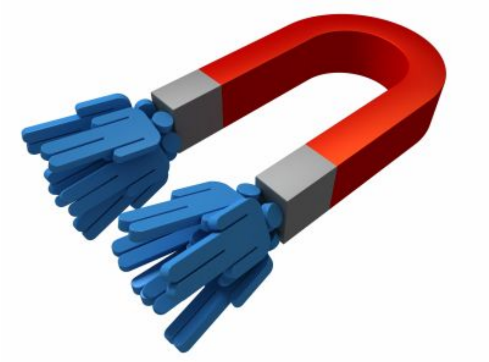


Source: https://www.fourquadrant.com/gartner-hype-cycles-magic-quadrants/

Peak of GHC & Effect on SDLC

Why Innovate at the Peak??

1) Spearhead Innovation
2) Boost Competitive Edge
3) Capture Market Share Early

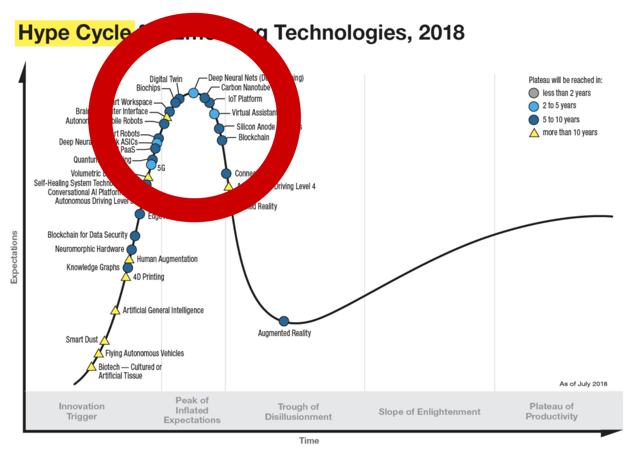


Effect of Investment At The Peak:

1) Surge of Pressure Top (Mgmt) to Down (Engg)
2) Increases risk of breaking safe SDLC

10 Phases of SDLC:

The Effect of Investing at The Peak of Inflated Expectations



Maximum Focus.
This is where we need the work done ….. **Fast**..

4. >>>>

5. Design: The How Part

6. Devel

What is going on here?
Who wrote this code & why?
Why is this not working !!!!

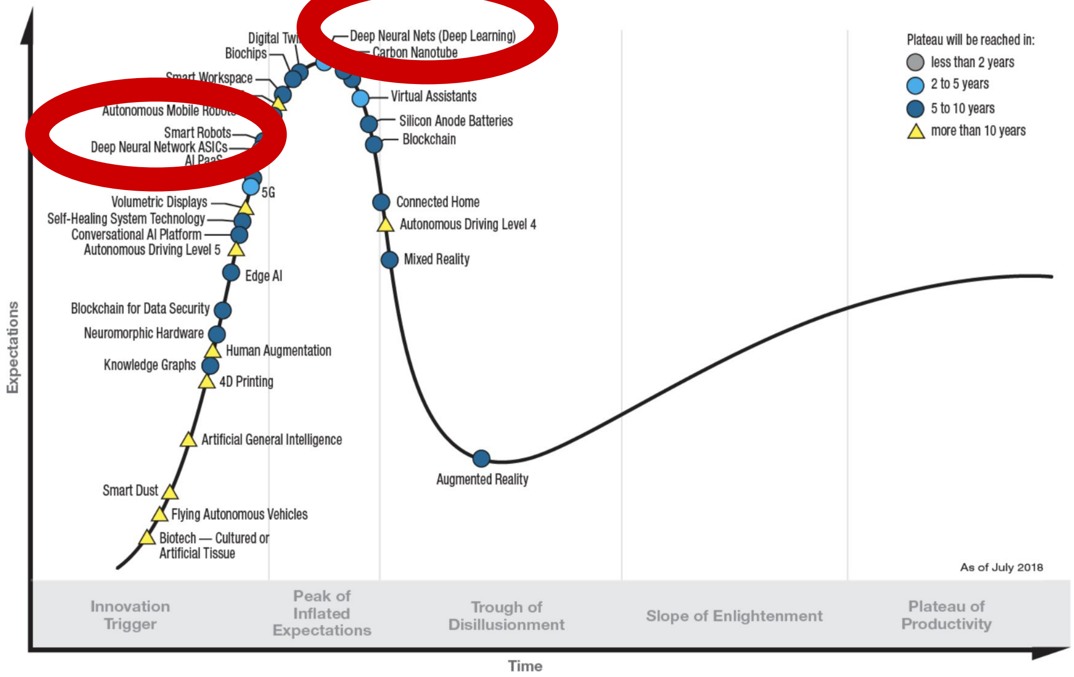
8.

9. Operation & **Maintenance**

10. Disposal : End of Life

Where is AI?

Hype Cycle for Emerging Technologies, 2018



Source: https://www.fourquadrant.com/gartner-hype-cycles-magic-quadrants/

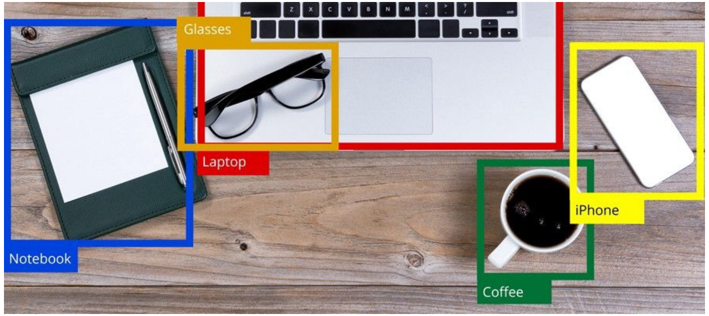
- In last 20y, academic papers increased by 9x
- AI startups increased from 2000 by 14x
- Annual investment in AI has increased by 4x since 2013

Source:
https://www.forbes.com/sites/louiscolumbus/2018/01/12/10-charts-that-will-change-your-perspective-on-artificial-intelligences-growth/#48f362674758

Basic Concepts

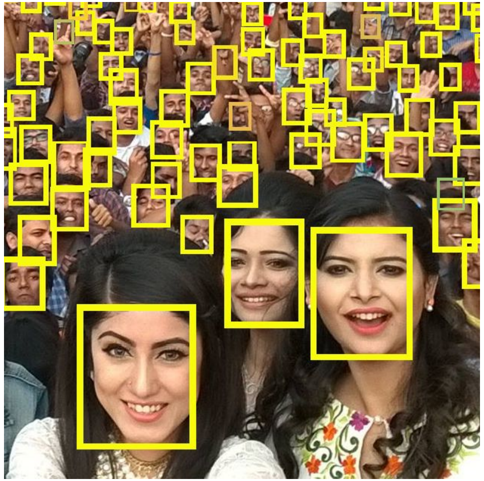
Object Detection:

- Task of localizing and detecting objects
- Traditional methods overtaken by AI



Face Detection:

- Subset of Object Detection: Localize & Detect Faces



Source:
https://towardsdatascience.com/beginners-guide-to-object-detection-algorithms-6620fb31c375
https://paperswithcode.com/task/face-detection/latest

Basic Concepts

Object Detection:
Different AI solutions come with tradeoffs:

a) Faster RCNN:

- Slow -> 2 Stage Network
- Accurate & Reliable

b) YOLO v3:

- Fast
- Sacrifices accuracy for speed
- Not versatile as network is intangible

c) SSD:

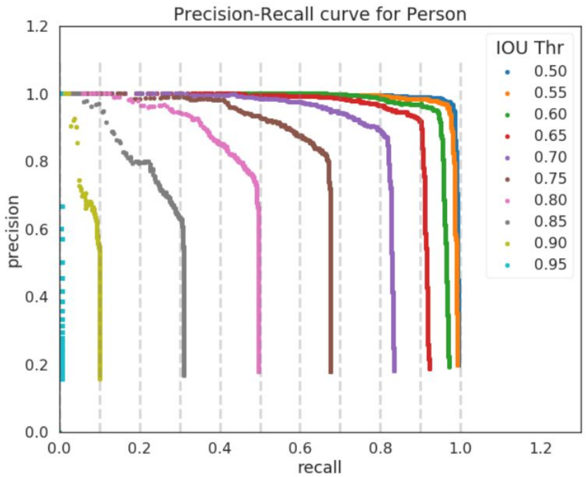
- Fast
- Sacrifices accuracy for speed
- Versatile as network is modularized

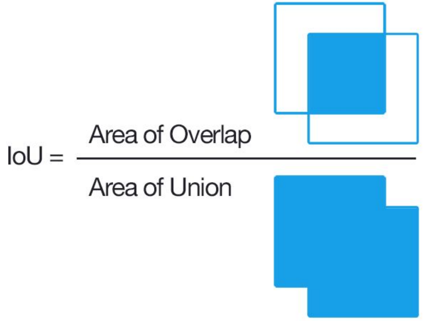
Basic Concepts

Evaluating Object Detection:

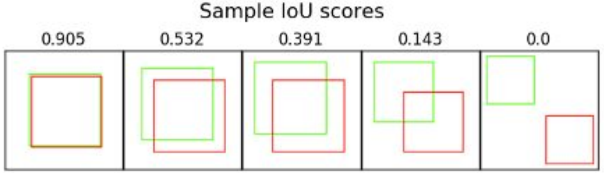
mean Average Precision @ IoU Threshold

- Area under the Precision-Recall Curve averaging over all classes and/or IoU values





IoU = Area of Overlap / Area of Union



Source: https://www.pyimagesearch.com/2016/11/07/intersection-over-union-iou-for-object-detection/

Source: http://ronny.rest/tutorials/module/localization_001/iou/

Source: https://medium.com/@timothycarlen/understanding-the-map-evaluation-metric-for-object-detection-a07fe6962cf3

Basic Concepts

Common AI Development Libraries:

TensorFlow

- Open Sourced by Google
- Steep Learning Curve
- Large community support

Caffe

- Open Sourced by UCB
- Closer to device
- Framework - Not a Dev Platform
- Large community support

PYTORCH

- Open Sourced by FB
- Easy to learn/Fast Prototyping
- Models can be converted to Caffe2
- Large community support

Case Study:

Deploy Face Detection on Smartphone

Supplier Co-MP -> Client Cu-MP

Requirements Discussion with Cu-MP

1. Should work on Cu-MP smartphones with specified hardware
2. Should not increase camera application’s memory beyond 768MB
3. OpenCV source code provided but modification through review process
4. Will provide annotated dataset for training
5. Will provide testing API to test on Cu-MP hidden test set (Max 24 submissions a day)
6. Should achieve mAP@0.5 of 70% at camera rate of 30FPS
7. Will provide 3 target smartphones for testing

Co-MP Implementation Plan

1. Engg team 2 members to work on optimizing OpenCV code

2. 2 Researchers allocated to find most stable and reliable deep learning algorithm

3. 4 Researchers allocated for implementation in PyTorch (favored by recent researchers) & Tensorflow (favored by senior researchers) (2 each) due to lack of clearness of which platform is better.

4. PyTorch & TF code can be converted to Caffe, so 2 Engineers allocated to optimize Caffe codebase

Progress Checkpoint

1. MobileNet v2 SSD Lite was selected. Used a more recent operation called Depthwise Separable Convolution used for model compression

2. Both (PyTorch & TF) teams achieved mAP of 76% at 25FPS

3. Major optimizations committed to OpenCV source code

4. Caffe source code optimizations in progress

Disaster Week Prior to Customer Demo

1. During integration camera application kept crashing ->
   Group convolution operation for depthwise separable convolution not implemented by Cu-MP compiler team although the SoC support present ->
   MobileNet v2 SSD Lite cannot be used

2. Plan B -> Implement SqueezeNet SSD in PyTorch (rapid prototyping)

3. 2 out of 4 researchers not skilled at PyTorch, hence were given minor tasks and mandatory participation in code reviews to ramp up quickly

4. Implementation occupied 830MB (62MB greater than reqm) but achieved mAP @ 0.5 of 65% at 23FPS

Salt on the Wound: Customer Demo

1. Cu-MP announces it recently added 10K more images to hidden test set -> Would give Co-MP 4 week extension

2. SqueezeNet SSD achieves meagre 55% mAP @ 0.5

3. Cu-MP presses that agreed reqm are strict

4. Cu-MP agrees to attempt to deliver the group convolution implementation but without guarantee

5. Cu-MP iterates deadlines are strict & does not heed to Co-MP extension requests

Firefight: Triage & Diagnosis

1. mAP drop due to lack of detection of small faces due to
    a) SSD architecture drawback
    b) Lack of small faces data points in training set

2. Engineering team interfaces with compiler team for group convolution operation

3. 2 researchers put in charge of performing architecture modifications for Squeezenet SSD. 2 researchers for Mobilenet v2 SSD Lite in case group convolution operation is successful

4. 2 engineering members assigned to collect & annotate small face & low light data (which was found to also be in small numbers)

Sigh of Relief: Final Product Delivery

1) Engg <-> Compiler team successful. Group convolution implemented

2) The customized Mobilenet v2 SSDLite achieved 72% map @ 0.5 at 30FPS

3) Success through architecture modifications due to research efforts, data augmentation & optimizations by engineering team

Case Study:

Post Mortem

Requirements Analysis: The Blank Cheque Problem

1) Not well researched technologies cannot be holistically evaluated through academic metrics

    e.g) Low light photography samples

2) Assumptions from successes of similar experiments cannot be extrapolated to other experiments

    e.g) mAP @ 0.5 of 70% blindly agreed even though mAP is a co-property of the dataset!

3) Requirements analysis must be conducted in the presence of senior research scientists with prior domain experience

4) Requirements analysis cannot be treated like a Blank Cheque!

Bias Towards Productionizing State of The Art

1) R & D team: Population(Researchers) > Population(Engineers)

2) Media hype focus on SOTA -> Translates to Expectations of Product

3) Leads to pushing SOTA into production without understanding limitations & environment requirements of the tech

   e.g) Using MobileNet v2 SSDLite (SOTA for lightweight object detection)
   without confirming if “Group Convolution” is implemented

Lack of Data First Mentality

1) Problem? Think of solution -> No!
   Problem? Understand data. Understand data representation. Think of Solution.

   e.g) Small faces & low light images absent -> Last minute find. High pressure.

2) Noisy data (Garbage) In -> Garbage Out

3) Data driven testing should be in parallel with solution scoping.

4) Encourages rail guarding of development & coverage oriented testing

Would **HIGHLY** recommend reading:
Z. C. Lipton and J. Steinhardt, “Troubling trends in machine learning scholarship,” Queue, vol. 17, no. 1, pp. 80:45–80:77, Feb. 2019.

Divide & Conquer: A Double Edged Sword

1) Software Project Management Process is different for software dev vs R&D projects i.e. Research projects are open ended & more flexible.

2) Requirement for effective task division ->
Delicate balance to handle cross - talent knowledge flow + task completion

e.g) Bifurcation into TF & PyTorch teams -> Redundant work, Talent Waste
Could have instead worked with toy examples to compare performance

Would **HIGHLY** recommend reading:

J. Kisielnicki, “Project management in research and development,” Foundations of Management, vol. 6, 12
2014.

Bridging Knowledge Gaps

1) High Reward & Low Risk Investment

2) Researchers are hired for their unique skill & hence R & D teams have silo-like skillsets (highly specialized)

3) Research -> Product involves convergence of highly skilled researchers with diverse experience & high variance of egos

4) Becomes critical to build ecosystem to bridge knowledge gaps:
   a) Formal training b) KT Sessions c) Pair Programming

   e.g) PyTorch/TF training sessions given to researchers for cross collaboration

Inducing Explicit Accountability Through Implicit Explainability

1) New Tech. Limitations & Strengths not fully known

2) Question everything-> Why is it working? Why is it not working? Has the entire solution space been covered? Under what conditions is it or is it not working?

3) Accountability can clarify liability, minimize risks & increase trust

4) Implicit Explainability through plug and play explainable modules like decision heat maps. Eliminate black box nature.

   e.g) Early detection of small face failure or low light under representation

Dearth of Specialized Management

1) Project Management(Software Dev) ≠ Project Management(R & D)

2) Usually Senior Dev Managers recruited for Project Management(R & D)-> May pose long term risks as research mgmt responsibilities vary

3) Suggest a co-management structure with sufficient collective experience in managing dev+test, possess domain expertise to make technically sound assumptions & uncover hidden requirements & must be open to technological transitions

e.g) Co-MP management lacked in handling most of the prev mentioned points and also buckled to Cu-MP deadline pressures

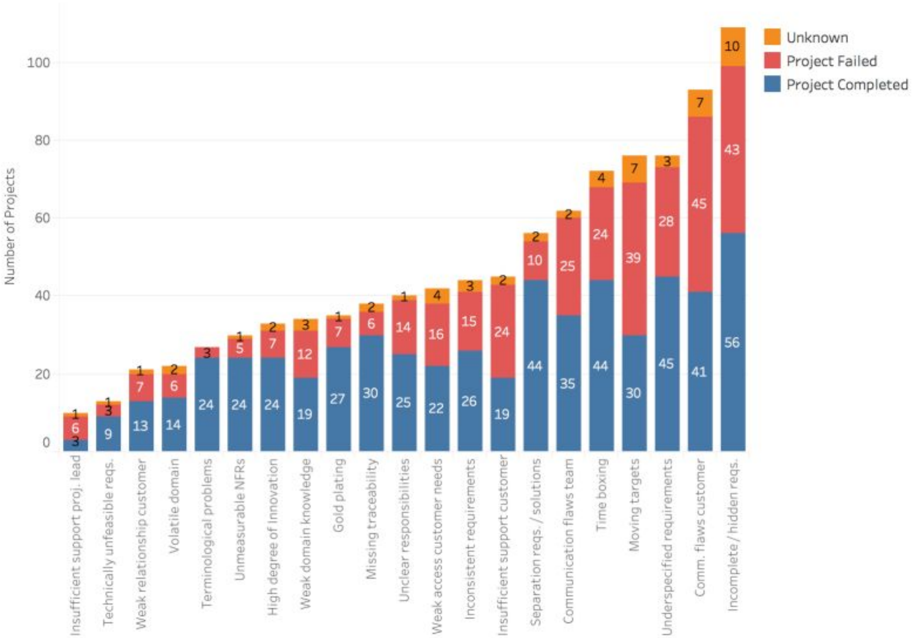
Post Mortem Summary:

R & D @ Peak of Inflated Expecations Should Watch Out For...

1. Meticulous Requirements Analysis: Don’t Sign on a Blank Cheque!
2. Productionize SOTA only when safe
3. Have a data first mentality
4. Manage Talent Pool Wisely
5. Do not cut back on bridging knowledge gaps
6. Add modules to perform implicit explainability to induce explicit accountability
7. Choose the right people to manage R&D

Conclusion:

Link to RE - Does this look familiar?



Source:

D. M. Fernandez, “Supporting requirements engineering research that industry needs: The naming the pain in requirements engineering initiative,” CoRR, vol. abs/1710.04630, 2017.

Thank You!

Q & A