## Machine Learning in Production

# Process and Technical Debt

# Process...

## Fundamentals of Engineering AI-Enabled Systems

**Holistic system view:** AI and non-AI components, pipelines, stakeholders, environment interactions, feedback loops

**Requirements:**
System and model goals
User requirements
Environment assumptions
Quality beyond accuracy
Measurement
Risk analysis
Planning for mistakes

**Architecture + design:**
Modeling tradeoffs
Deployment architecture
Data science pipelines
Telemetry, monitoring
Anticipating evolution
Big data processing
Human-AI design

**Quality assurance:**
Model testing
Data quality
QA automation
Testing in production
Infrastructure quality
Debugging

**Operations:**
Continuous deployment
Contin. experimentation
Configuration mgmt.
Monitoring
Versioning
Big data
DevOps, MLOps

**Teams and process:** Data science vs software eng. workflows, interdisciplinary teams, collaboration points, technical debt

## Responsible AI Engineering

- Provenance, versioning, reproducibility
- Safety
- Security and privacy
- Fairness
- Interpretability and explainability
- Transparency and trust

Ethics, governance, regulation, compliance, organizational culture

# Readings

Required Reading:

- Alex Serban, Koen van der Blom, Holger Hoos, and Joost Visser. 2020. "Adoption and Effects of Software Engineering Best Practices in Machine Learning." In Proceedings of the 14th ACM / IEEE International Symposium on Empirical Software Engineering and Measurement (ESEM) (ESEM '20).

Suggested Readings:

- Fowler and Highsmith. The Agile Manifesto
- Steve McConnell. Software project survival guide. Chapter 3
- Kruchten, Philippe, Robert L. Nord, and Ipek Ozkaya. "Technical debt: From metaphor to theory and practice." IEEE Software 29, no. 6 (2012): 18-21.

# Learning Goals

- Overview of common data science workflows (e.g., CRISP-DM)
  - Importance of iteration and experimentation
  - Role of computational notebooks in supporting data science workflows
- Overview of software engineering processes and lifecycles: costs and benefits of process, common process models, role of iteration and experimentation
- Contrasting data science and software engineering processes, goals and conflicts
- Integrating data science and software engineering workflows in process model for engineering AI-enabled systems with ML and non-ML components; contrasting different kinds of AI-enabled systems with data science trajectories
- Overview of technical debt as metaphor for process management; common sources of technical debt in AI-enabled systems

# What is Process?

# Software Process

*“The set of activities and associated results that produce a software product”*

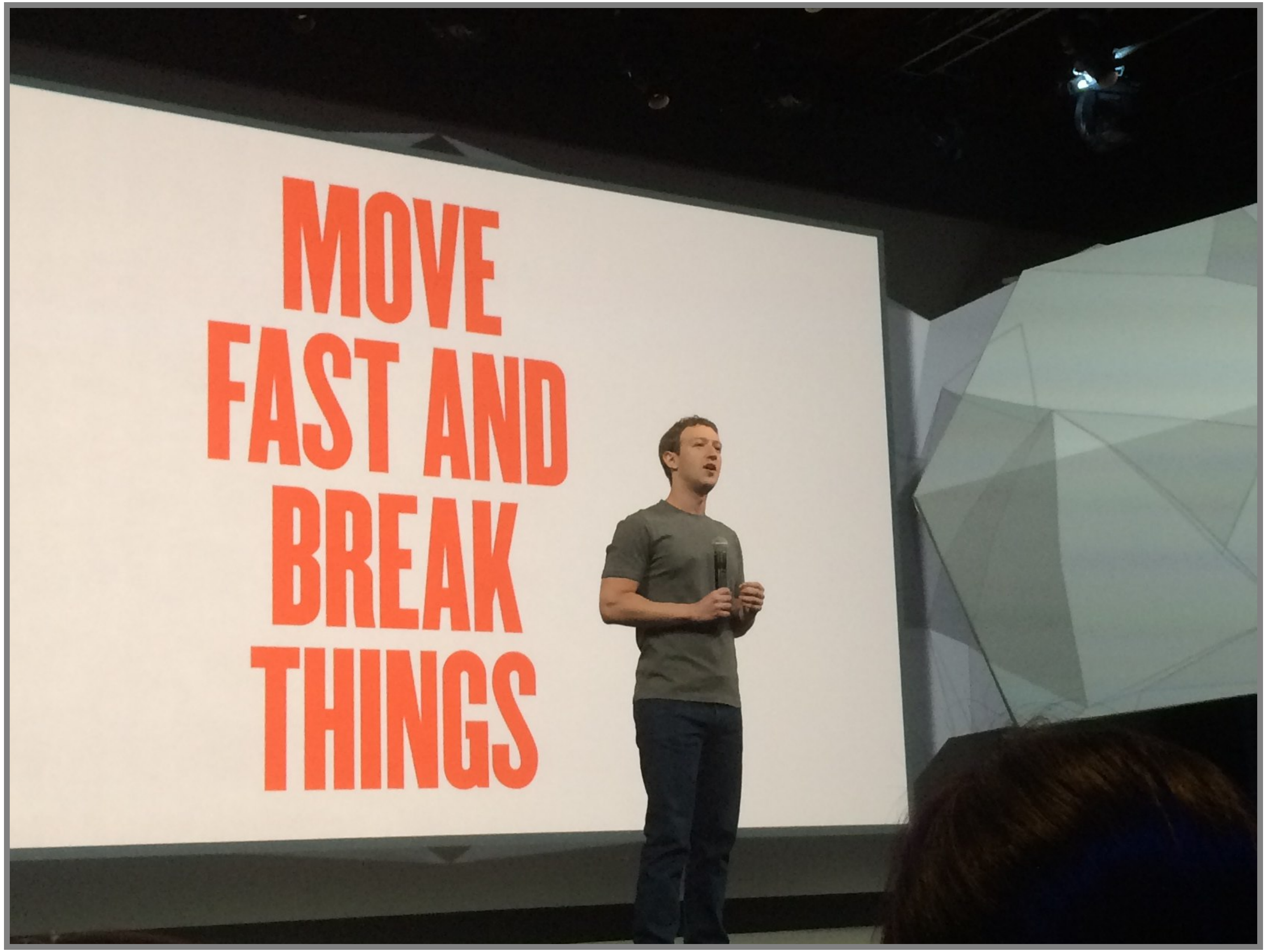
*A structured, systematic way of carrying out these activities*

**Q. Examples?**

Speaker notes

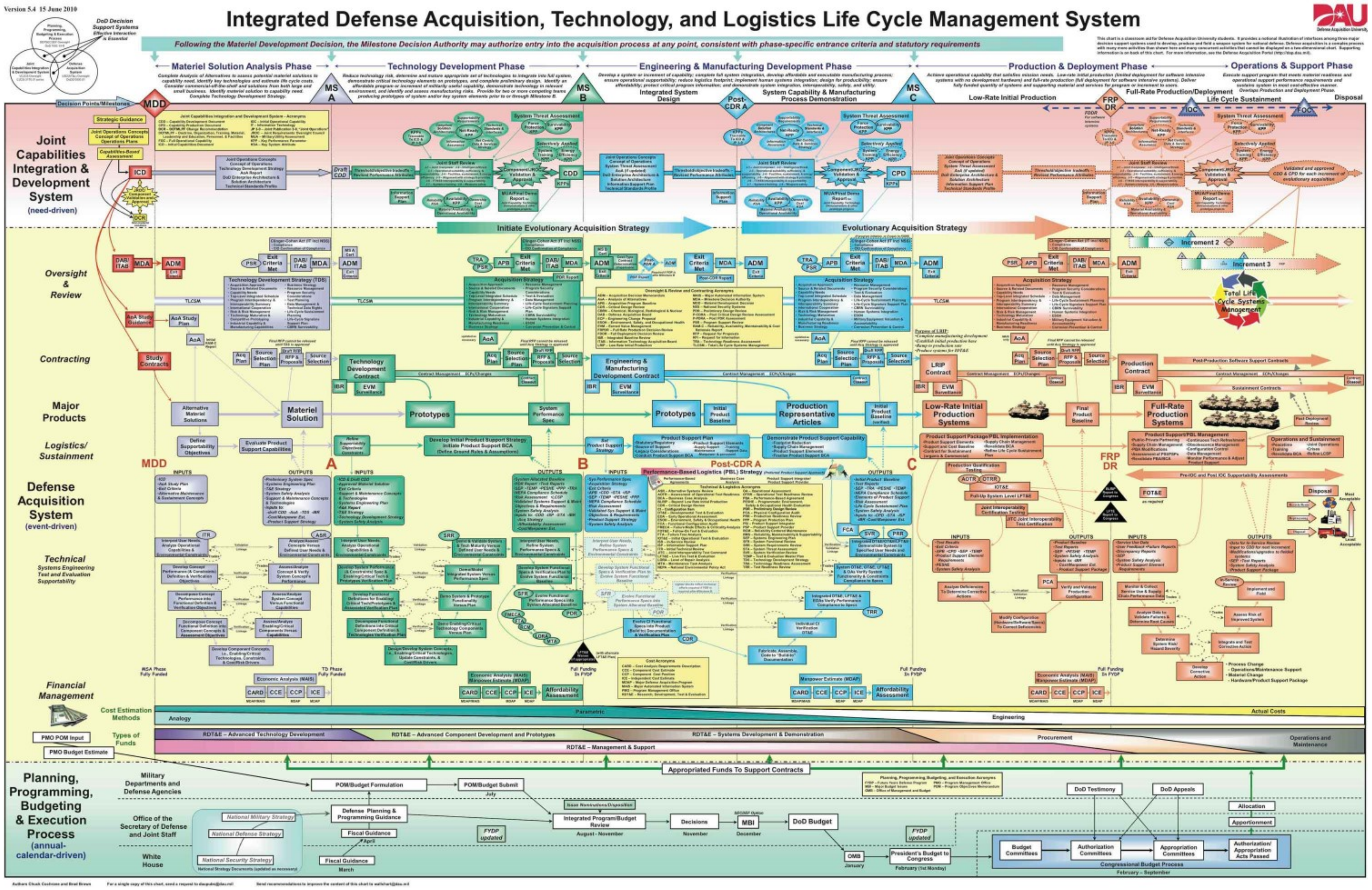
Writing down all requirements Require approval for all changes to requirements Use version control for all changes Track all reported bugs Review requirements and code Break down development into smaller tasks and schedule and monitor them Planning and conducting quality assurance Have daily status meetings Use Docker containers to push code between developers and operation

# Developers dislike processes


MOVE
FAST AND
BREAK
THINGS


We've changed our internal motto from "Move fast and break things" to "Move fast with stable infrastructure."
— Mark Zuckerberg —
AZ QUOTES

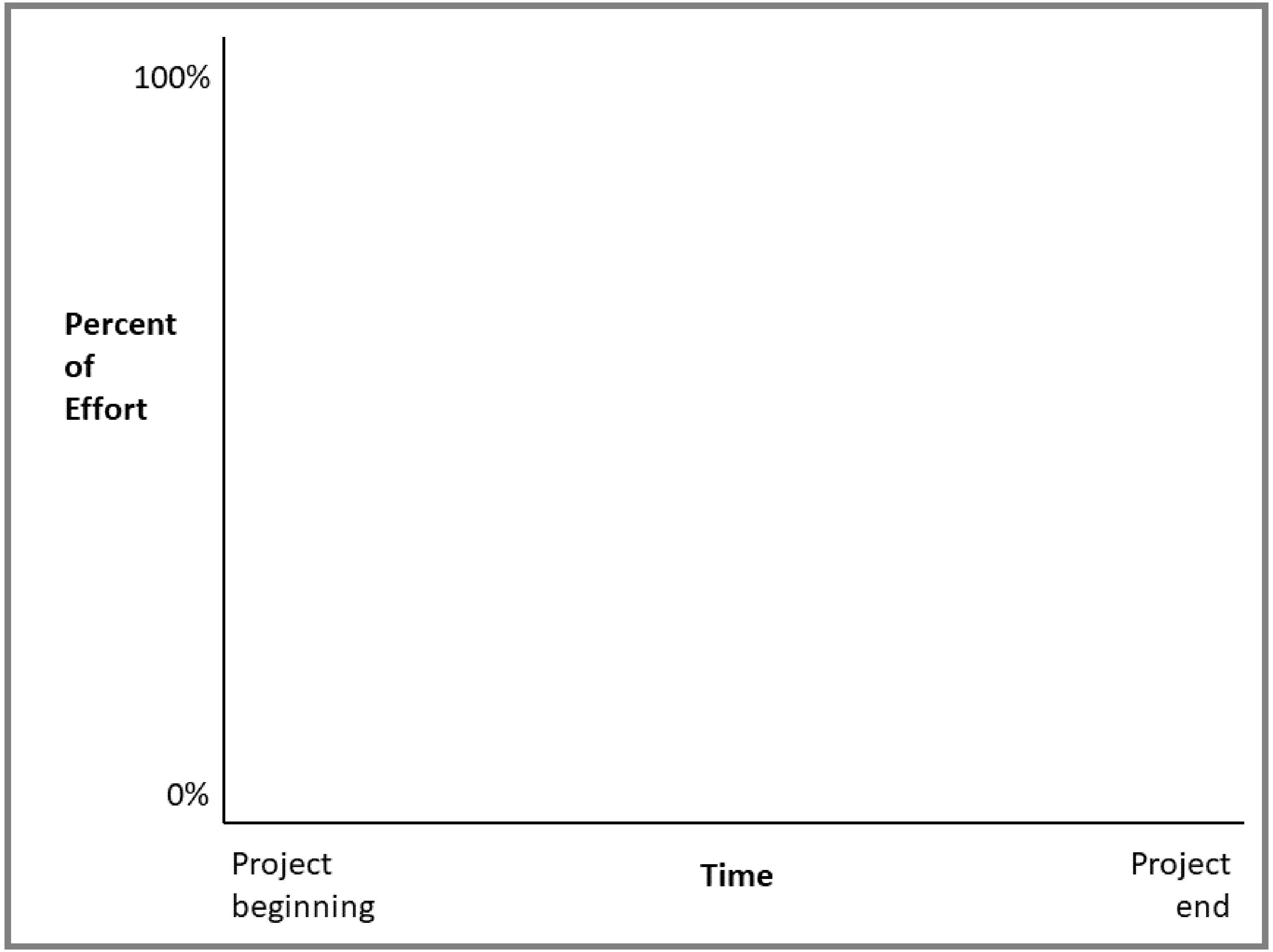
# Developers' view of processes



Speaker notes

Complicated processes like these are often what people associate with "process". Software process is needed, but does not need to be complicated.

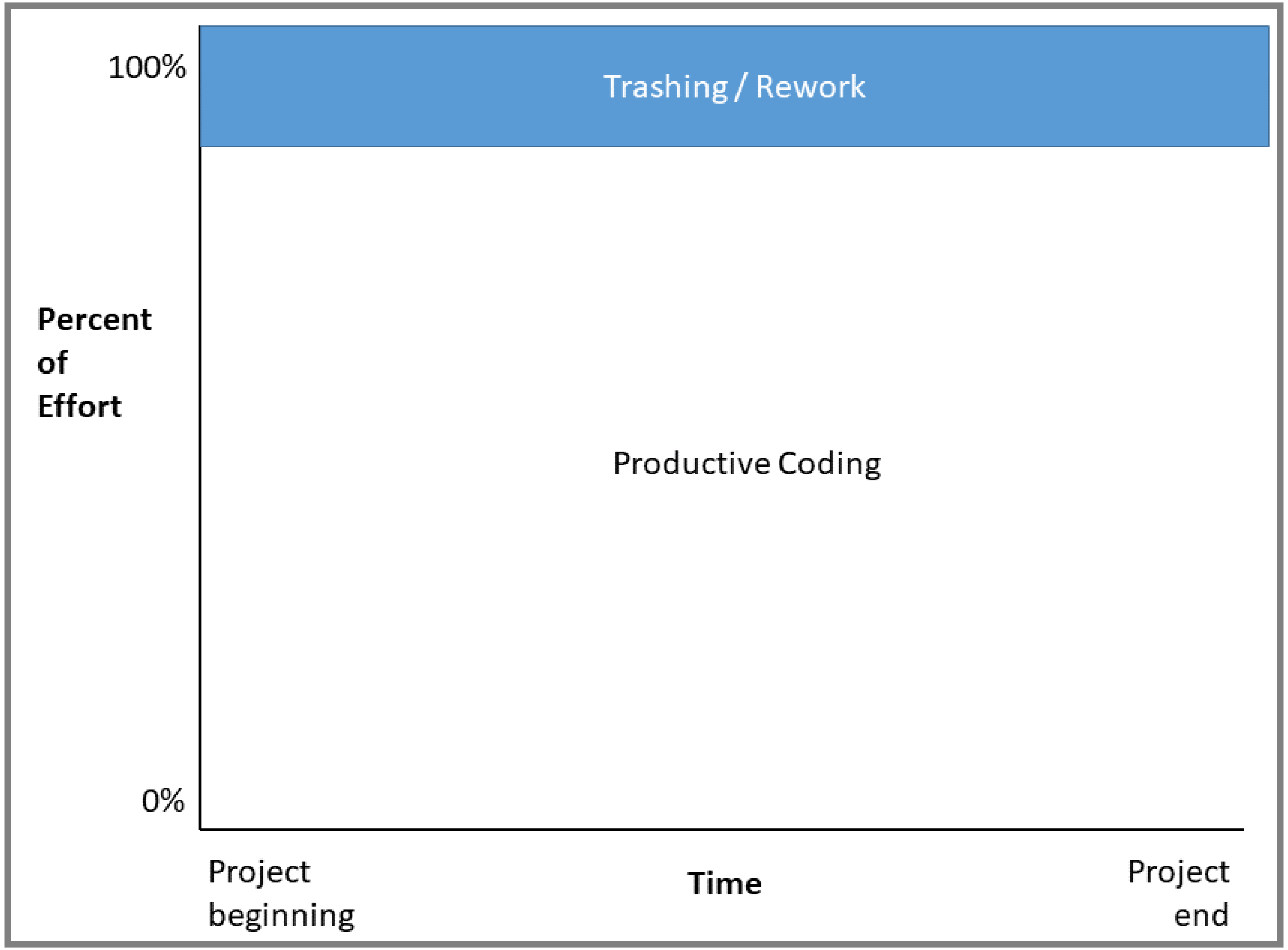
# What developers want



Speaker notes

Visualization following McConnell, Steve. Software project survival guide. Pearson Education, 1998.

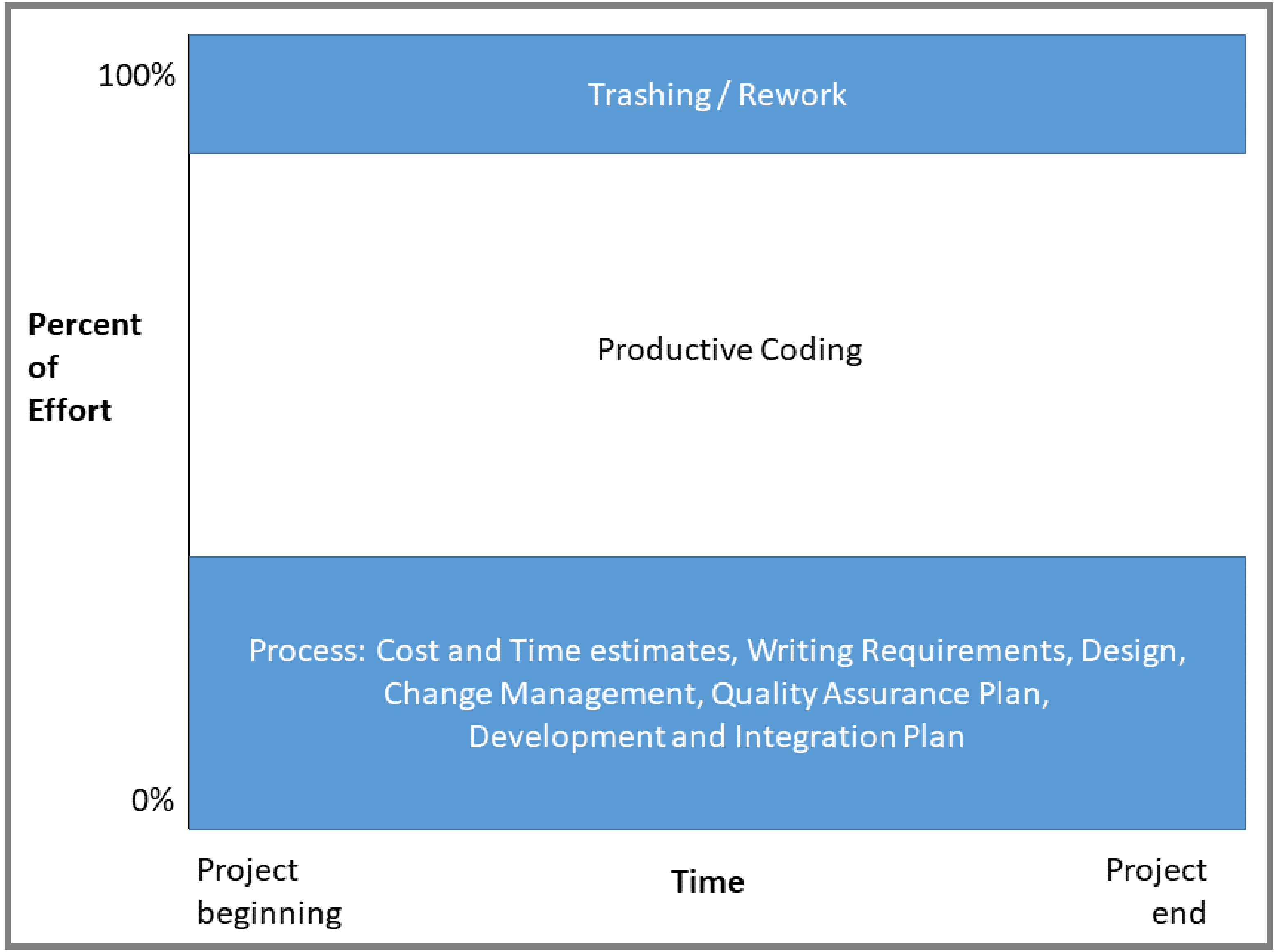
# What developers want



Speaker notes

Idea: spent most of the time on coding, accept a little rework

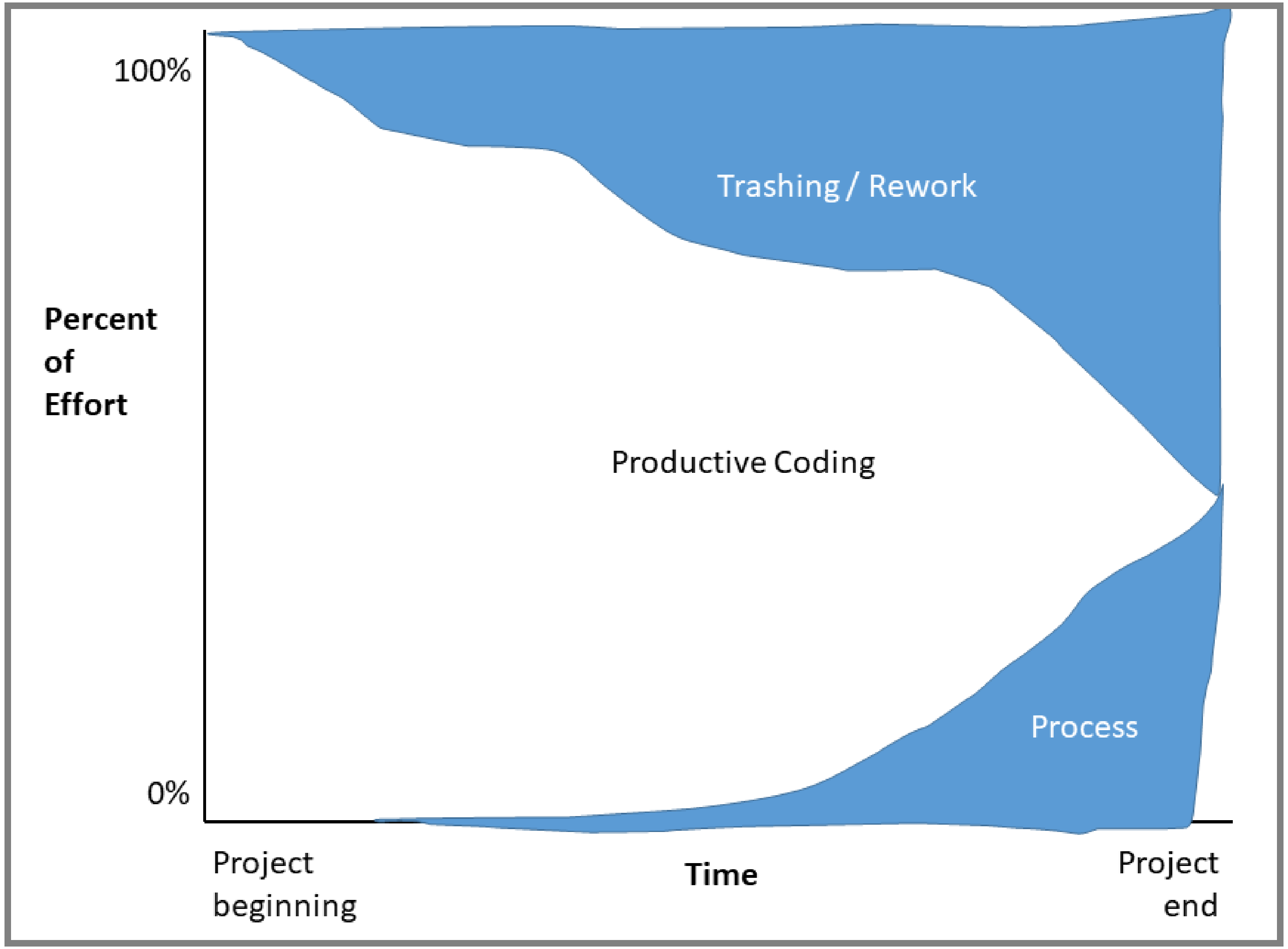
# What developers think of processes



Speaker notes

negative view of process. pure overhead, reduces productive work, limits creativity

# What eventually happens anyway



Speaker notes

Real experience if little attention is payed to process: increasingly complicated, increasing rework; attempts to rescue by introducing process

# Survival Mode

Missed deadlines -> "solo development mode" to meet own deadlines

Ignore integration work

Stop interacting with testers, technical writers, managers, ...

-> Results in further project delays, added costs, poor product quality...

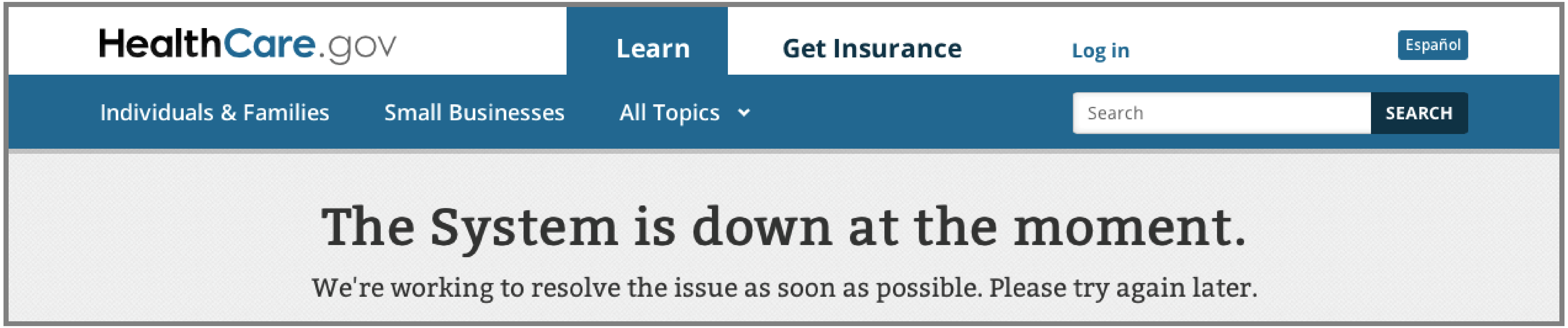
# Example of Process Problems?

Speaker notes

Collect examples of what could go wrong:

Change Control: Mid-project informal agreement to changes suggested by customer or manager. Project scope expands 25-50% Quality Assurance: Late detection of requirements and design issues. Test-debug-reimplement cycle limits development of new features. Release with known defects. Defect Tracking: Bug reports collected informally, forgotten System Integration: Integration of independently developed components at the very end of the project. Interfaces out of sync. Source Code Control: Accidentally overwritten changes, lost work. Scheduling: When project is behind, developers are asked weekly for new estimates.

# Example: Healthcare.gov

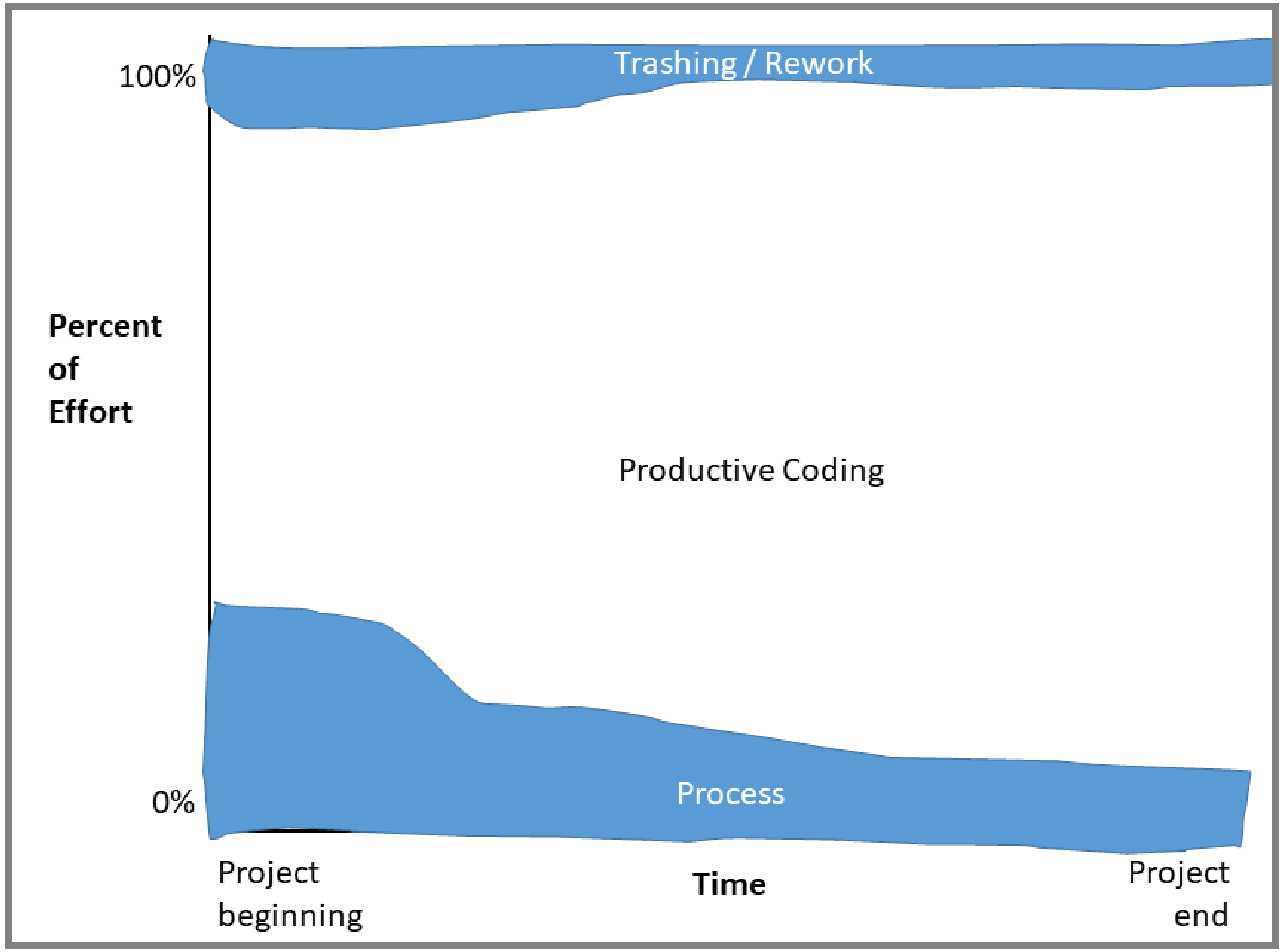



- Launched Oct, 2013; high demand (5x expected) causes site crash
- UI incomplete (e.g., missing drop-down menu); missing/incomplete insurance data; log-in system also crashed for IT technicians
- On 1st day, 6 users managed to register
- Initial budget: 93.7M USD; Final cost: 1.7B

# Example: Healthcare.gov

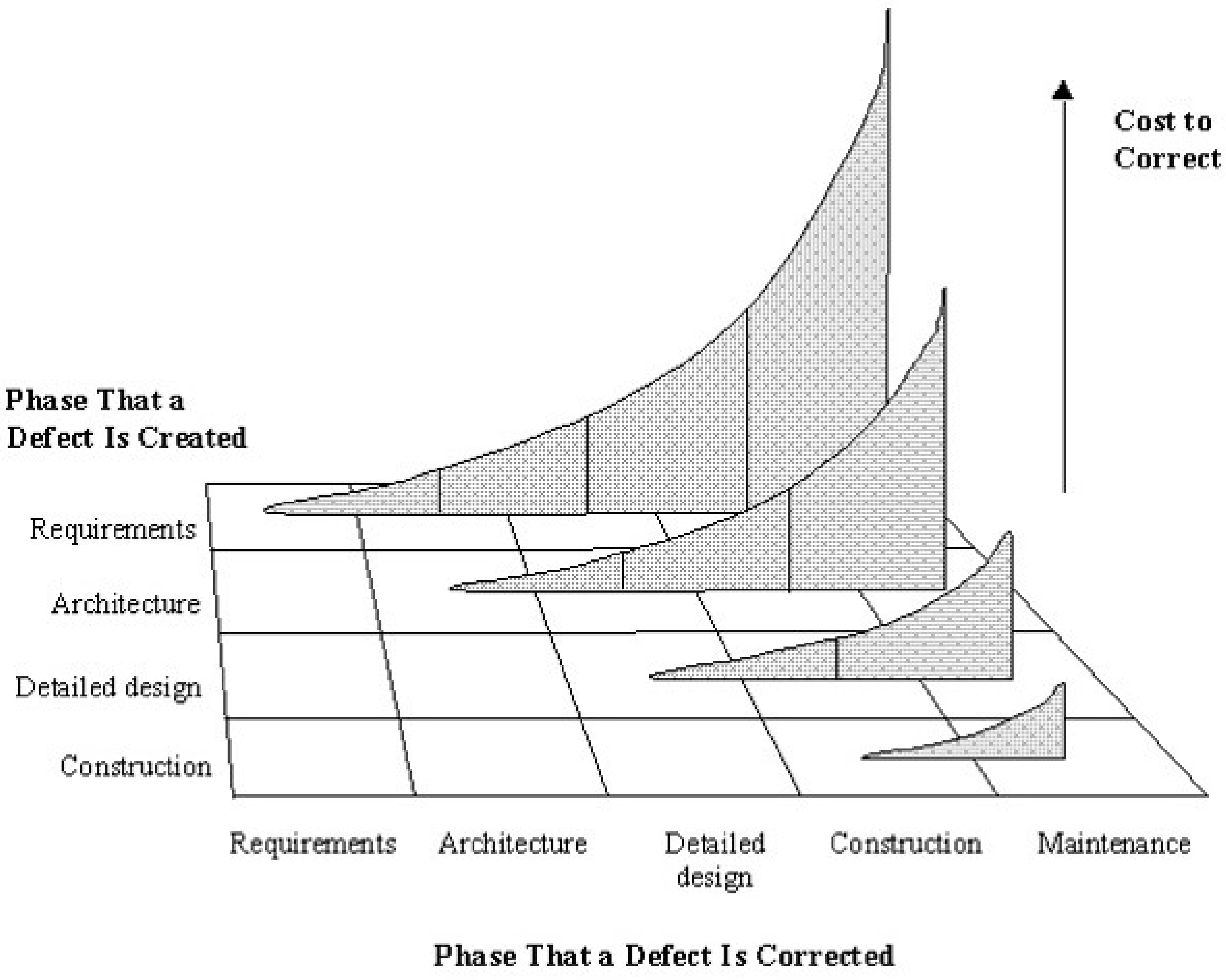
- Lack of experience: "*...and project managers had little knowledge on the amount of work required and typical product development processes*"
- Lack of leadership: "*...no formal division of responsibilities in place...a lack of communication when key decisions were made*"
- Schedule pressure: "*...employees were pressured to launch on time regardless of completion or the amount (and results) of testing*"

# *Hypothesis: Process increases flexibility and efficiency + Upfront investment for later greater returns*



Speaker notes

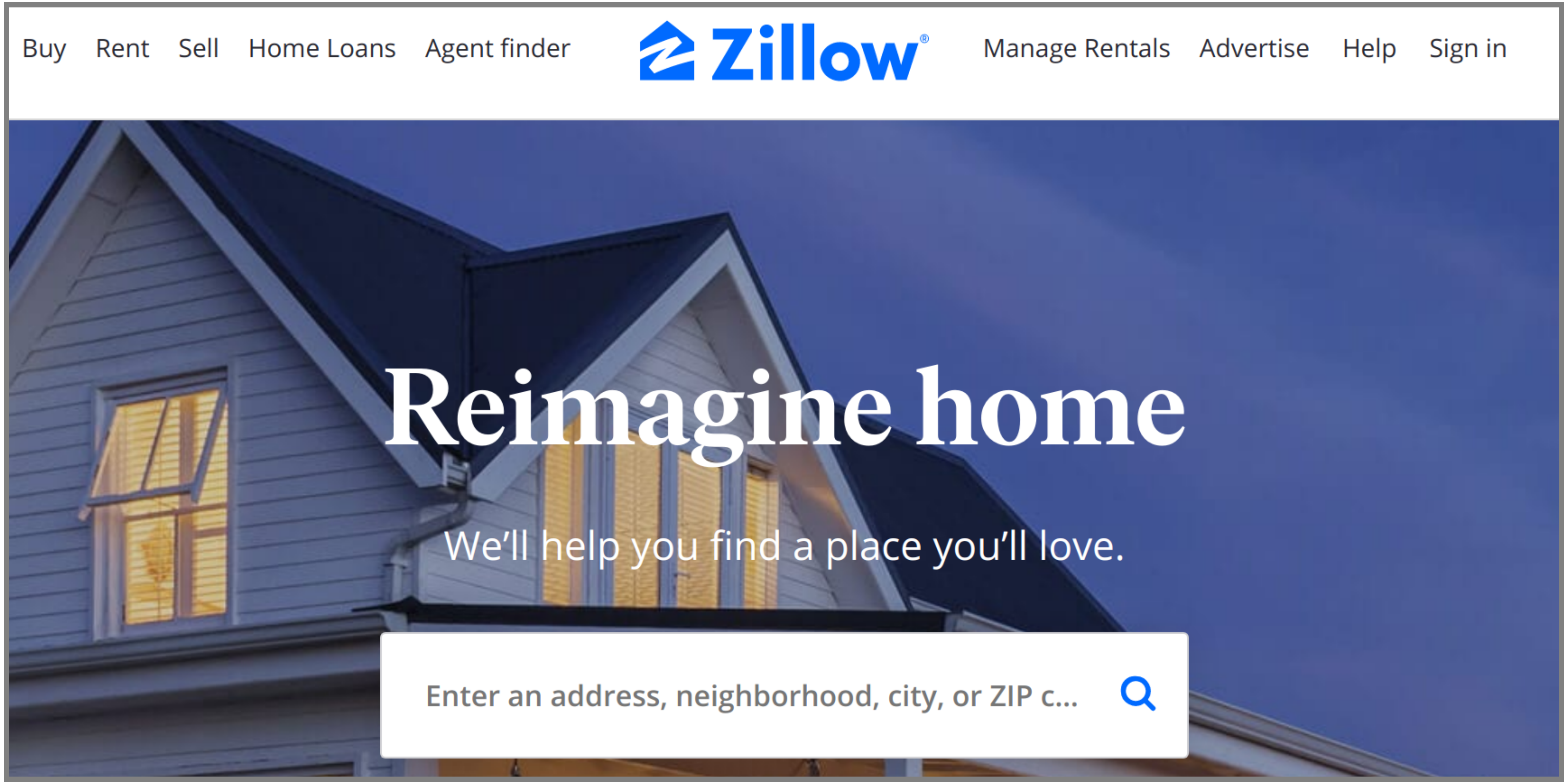
ideal setting of little process investment upfront


Cost to
Correct
Phase That a
Defect Is Created
Requirements
Architecture
Detailed design
Construction
Requirements
Architecture
Detailed
design
Construction
Maintenance
Phase That a Defect Is Corrected

Speaker notes

Empirically well established rule: Bugs are increasingly expensive to fix the larger the distance between the phase where they are created vs where they are corrected.

# Case Study: Real Estate Website



# ML Component: Predicting Real Estate Value

Given a large database of house sales and statistical/demographic data from public records, predict the sales price of a house.

$$f(size, rooms, tax, neighborhood, \ldots) \rightarrow price$$

# What's your process?

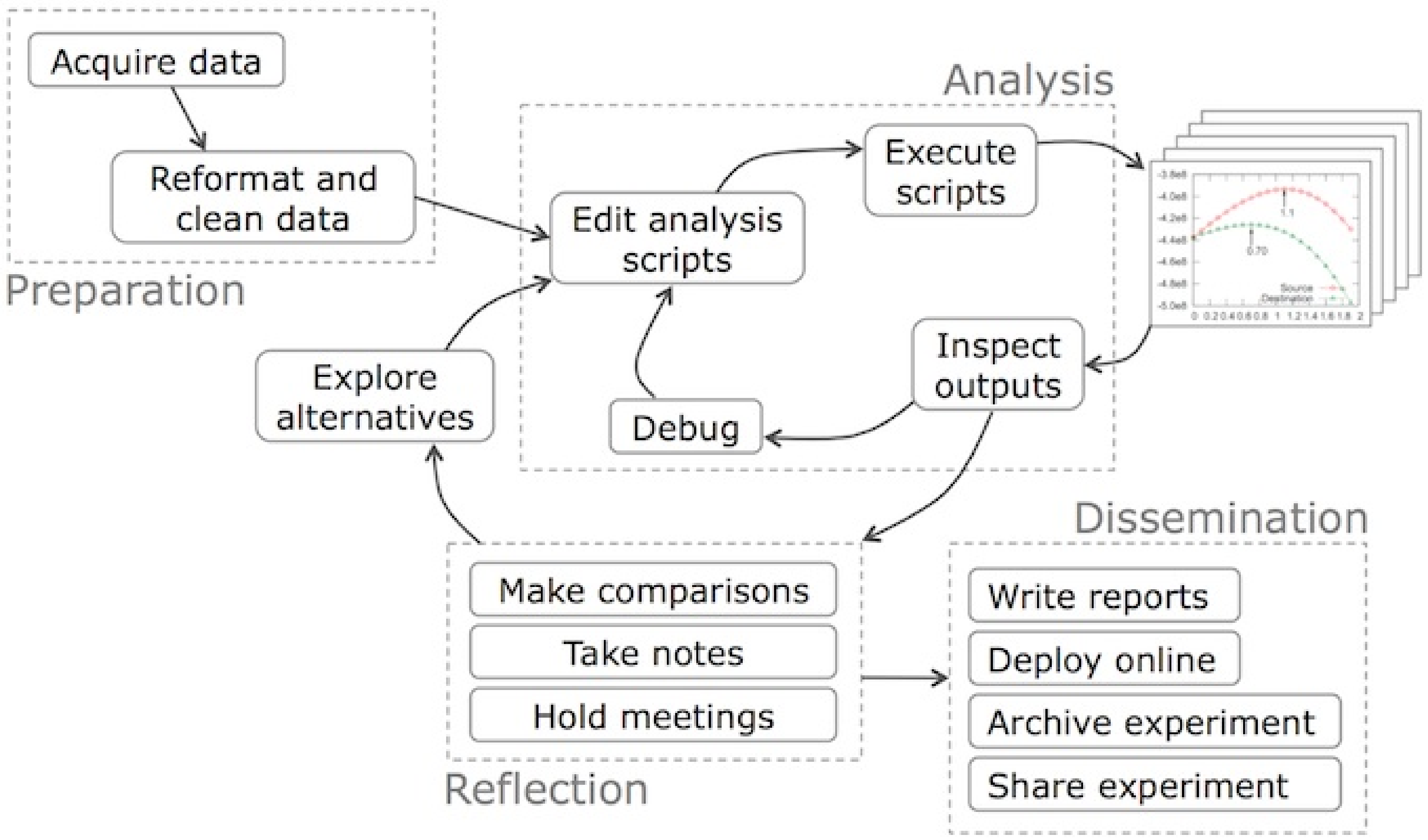
## Q. What steps would you take to build this component?

# Exploratory Questions

- What exactly are we trying to model and predict?
- What types of data do we need?
- What type of model works the best for this problem?
- What are the right metrics to evaluate the model performance?
- What is the user actually interested in seeing?
- Will this product actually help with the organizational goals?
- ...

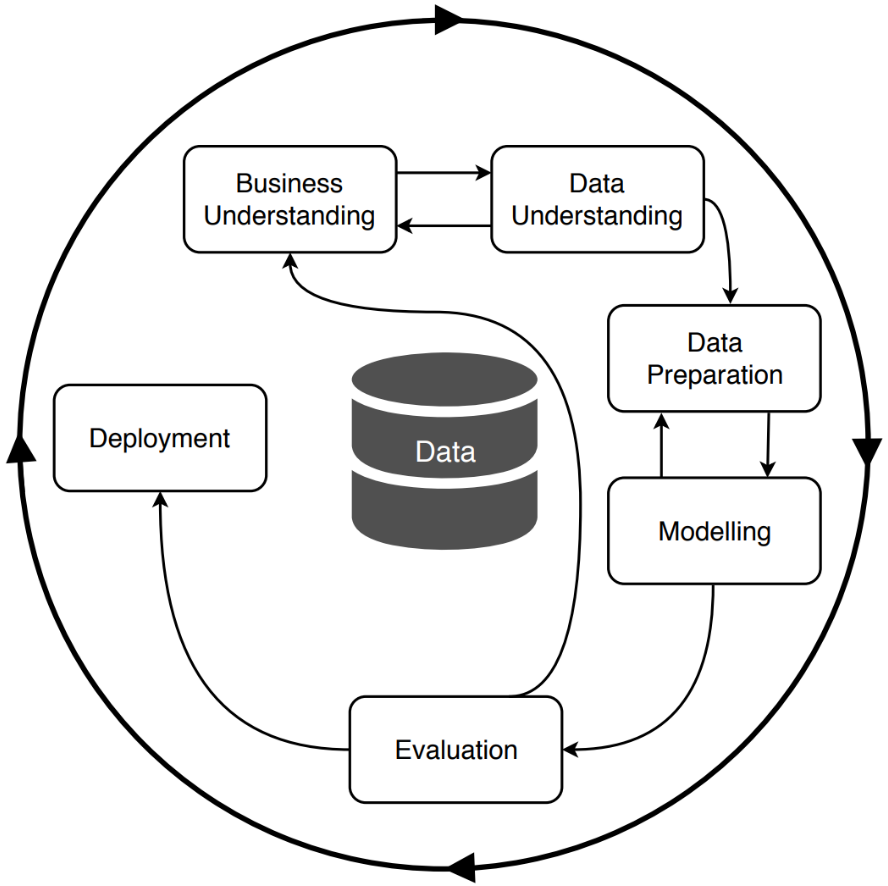
# Data Science: Iteration and Exploration

# Data Science is Iterative and Exploratory




≡ Source: Guo. "[Data Science Workflow: Overview and Challenges](#)." Blog@CACM, Oct 2013

# Data Science is Iterative and Exploratory




Martínez-Plumed et al. "CRISP-DM Twenty Years Later: From Data Mining Processes to Data Science Trajectories." IEEE Transactions on Knowledge and Data Engineering (2019).

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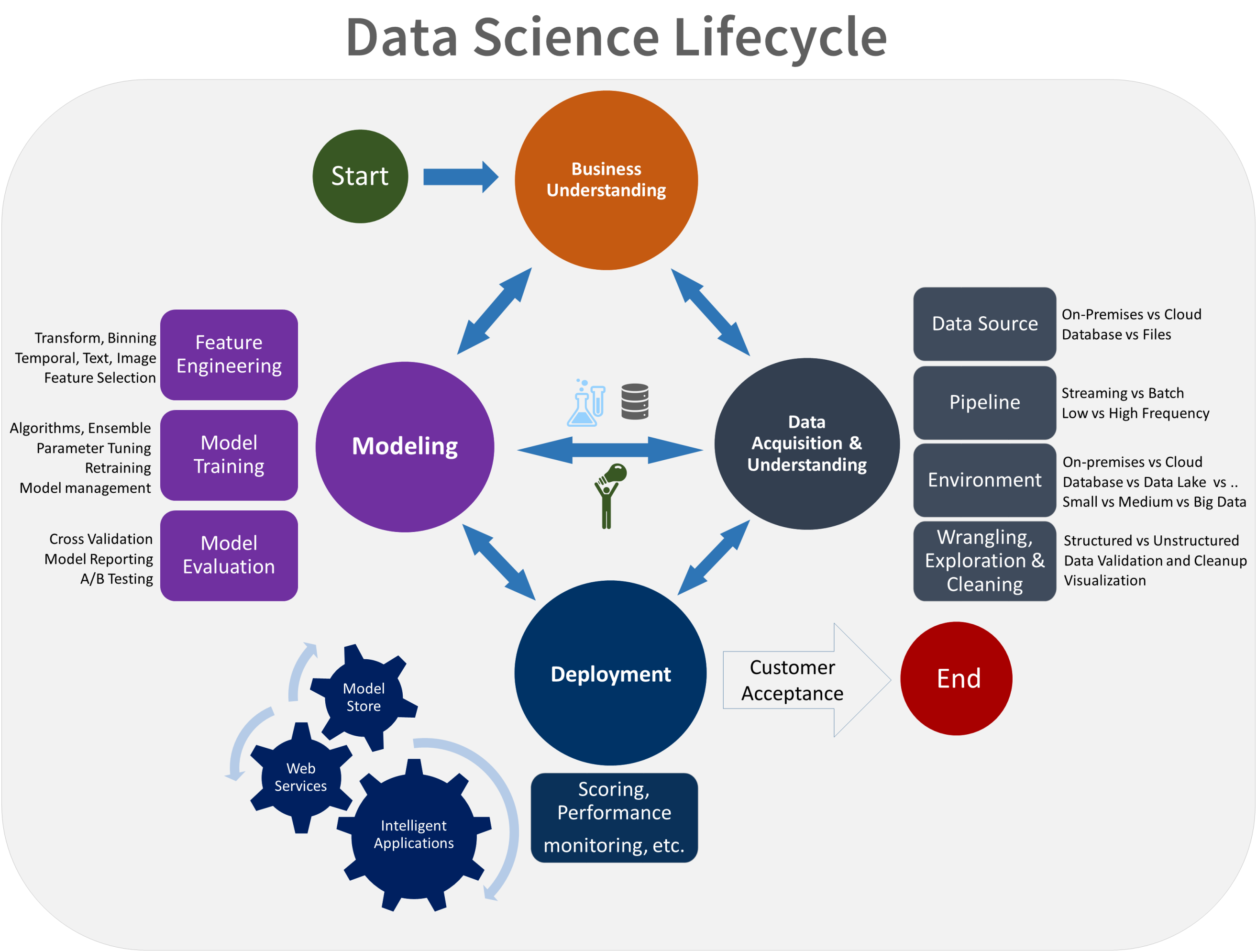
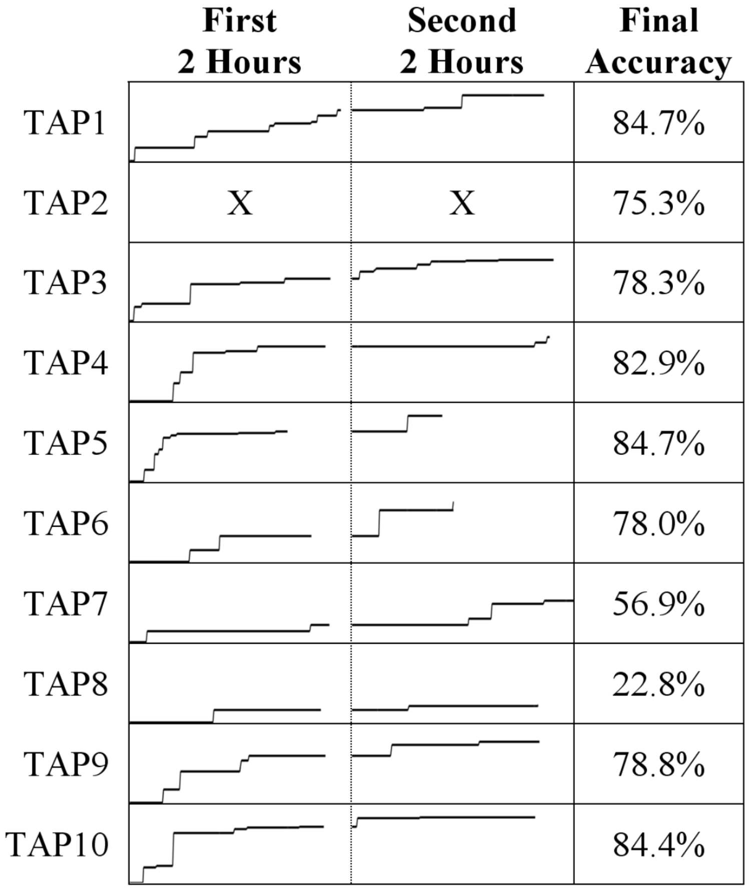



Microsoft Azure Team, "What is the Team Data Science Process?" Microsoft Doc., Jan 2020

# Data Science is Iterative and Exploratory




Source: Patel, Kayur, James Fogarty, James A. Landay, and Beverly Harrison. "Investigating statistical machine learning as a tool for software development." In Proc. CHI, 2008.

Speaker notes

This figure shows the result from a controlled experiment in which participants had 2 sessions of 2h each to build a model. Whenever the participants evaluated a model in the process, the accuracy is recorded. These plots show the accuracy improvements over time, showing how data scientists make incremental improvements through frequent iteration.

# Data Science is Iterative and Exploratory

Science mindset: start with rough goal, no clear specification, unclear whether possible

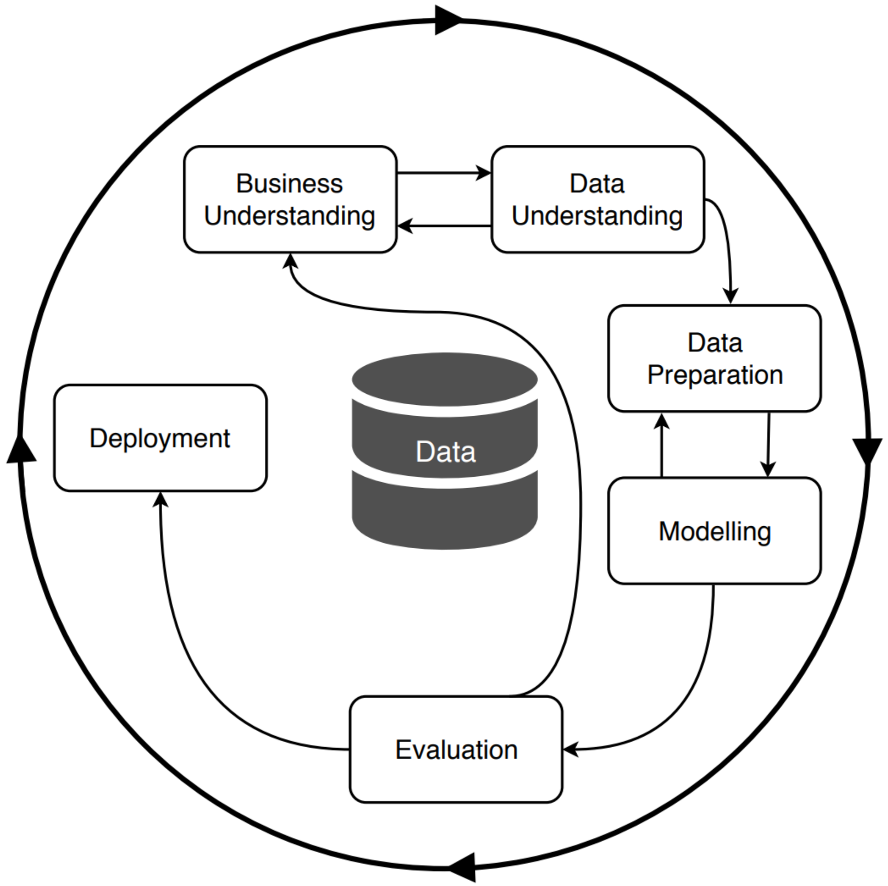
Heuristics and experience to guide the process

Try and error, refine iteratively, hypothesis testing

Go back to data collection and cleaning if needed, revise goals

# Share Experience?

# Different Trajectories

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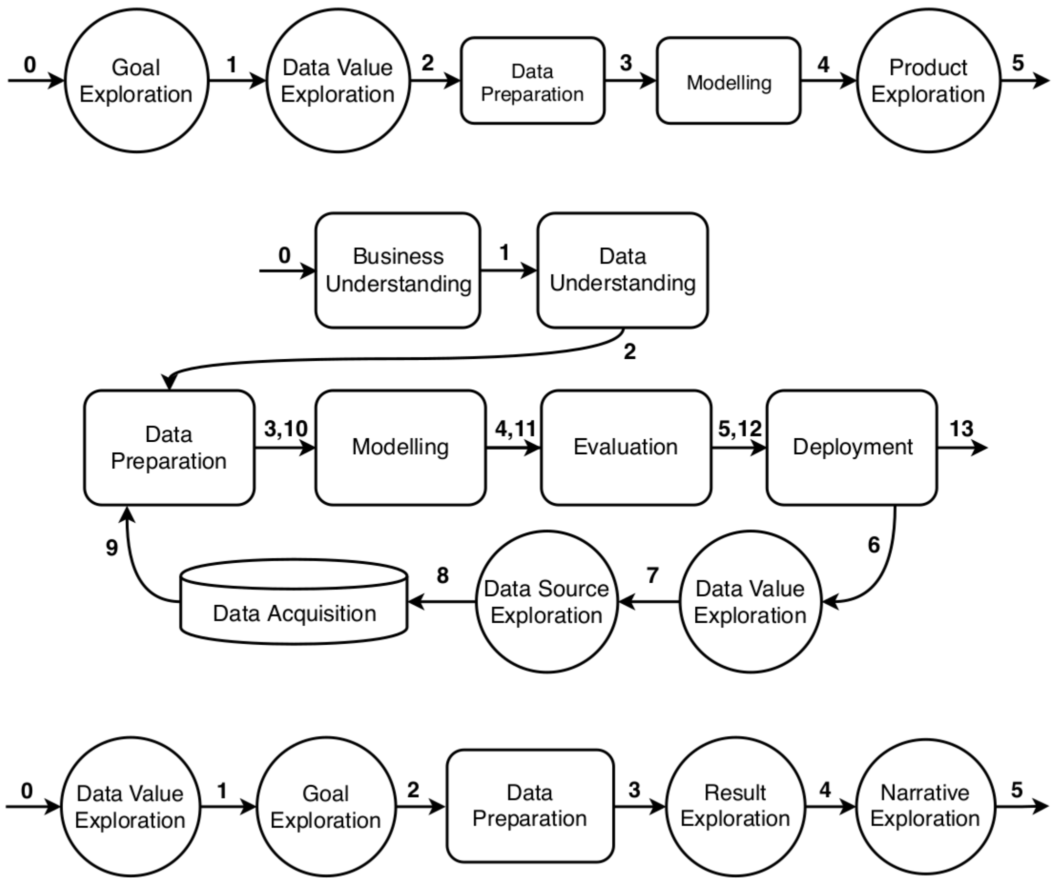
# Different Trajectories




From: Martínez-Plumed et al. "CRISP-DM Twenty Years Later: From Data Mining Processes to Data Science Trajectories." IEEE Transactions on Knowledge and Data Engineering (2019).

Speaker notes

- A product to recommend trips connecting tourist attractions in a town may be based on location tracking data collected by navigation and mapping apps. To build such a project, one might start with a concrete goal in mind and explore whether enough user location history data is available or can be acquired. One would then go through traditional data preparation and modeling stages before exploring how to best present the results to users.
- An insurance company tries to improve their model to score the risk of drivers based on their behavior and sensors in their cars. Here an existing product is to be refined and a better understanding of the business case is needed before diving into the data exploration and modeling. The team might spend significant time in exploring new data sources that may provide new insights and may debate the cost and benefits of this data or data gathering strategy (e.g., installing sensors in customer cars).
- A credit card company may want to sell data about what kind of products different people (nationalities) tend to buy at different times and days in different locations to other companies (retailers, restaurants). They may explore existing data without yet knowing what kind of data may be of interest to what kind of customers. They may actively search for interesting narratives in the data, posing questions such as “Ever wondered when the French buy their food?” or “Which places the Germans flock to on their holidays?” in promotional material.

# Computational Notebooks

- Origins in "literate programming", interleaving text and code, treating programs as literature (Knuth'84)
- First notebook in Wolfram Mathematica 1.0 in 1988
- Document with text and code cells, showing execution results under cells
- Code of cells is executed, per cell, in a kernel
- Many notebook implementations and supported languages, Python + Jupyter currently most popular

```
# load data collected from team1
import pandas as pd


url = 'http://128.2.25.78:8080/private/log1.clean'
df = pd.read_csv(url)
df.head()
```

| | dayIdx | user | userAvgTime | location | dow | isWeekend | time |
|---|---|---|---|---|---|---|---|
| **0** | 0 | Pittsburgh66Correy | 7.045001 | Pittsburgh | 6 | True | 0.000000 |
| **1** | 1 | Pittsburgh66Correy | 7.045001 | Pittsburgh | 7 | True | 6.883333 |
| **2** | 2 | Pittsburgh66Correy | 7.045001 | Pittsburgh | 1 | False | 6.816667 |
| **3** | 3 | Pittsburgh66Correy | 7.045001 | Pittsburgh | 2 | False | 7.383333 |
| **4** | 4 | Pittsburgh66Correy | 7.045001 | Pittsburgh | 3 | False | 0.000000 |

Data was preprocessed externally, identifying the time at a given day when the light was first turned on
12pm). Weather and sunrise information is not included here, though that'd be important. If the light w
this morning (quite common), 0 is recorded.

```
[ ] # just data encoding and splitting X and Y

    X = df.drop(['time'], axis=1)
    YnonZero = df['time'] > 0
    Y = df['time']

    from sklearn import preprocessing
    # leDate = preprocessing.LabelEncoder()
    # leDate.fit(X['date'])
    # leDate.transform(X['date'])

    X=X.apply(preprocessing.LabelEncoder().fit_transform)
    X
```

Speaker notes

- See also https://en.wikipedia.org/wiki/Literate_programming
- Demo with public notebook, e.g., https://colab.research.google.com/notebooks/mlcc/intro_to_pandas.ipynb

# Notebooks Support Iteration and Exploration

Quick feedback, similar to REPL

Visual feedback including figures and tables

Incremental computation: reexecuting individual cells

Quick and easy: copy paste, no abstraction needed

Easy to share: document includes text, code, and results

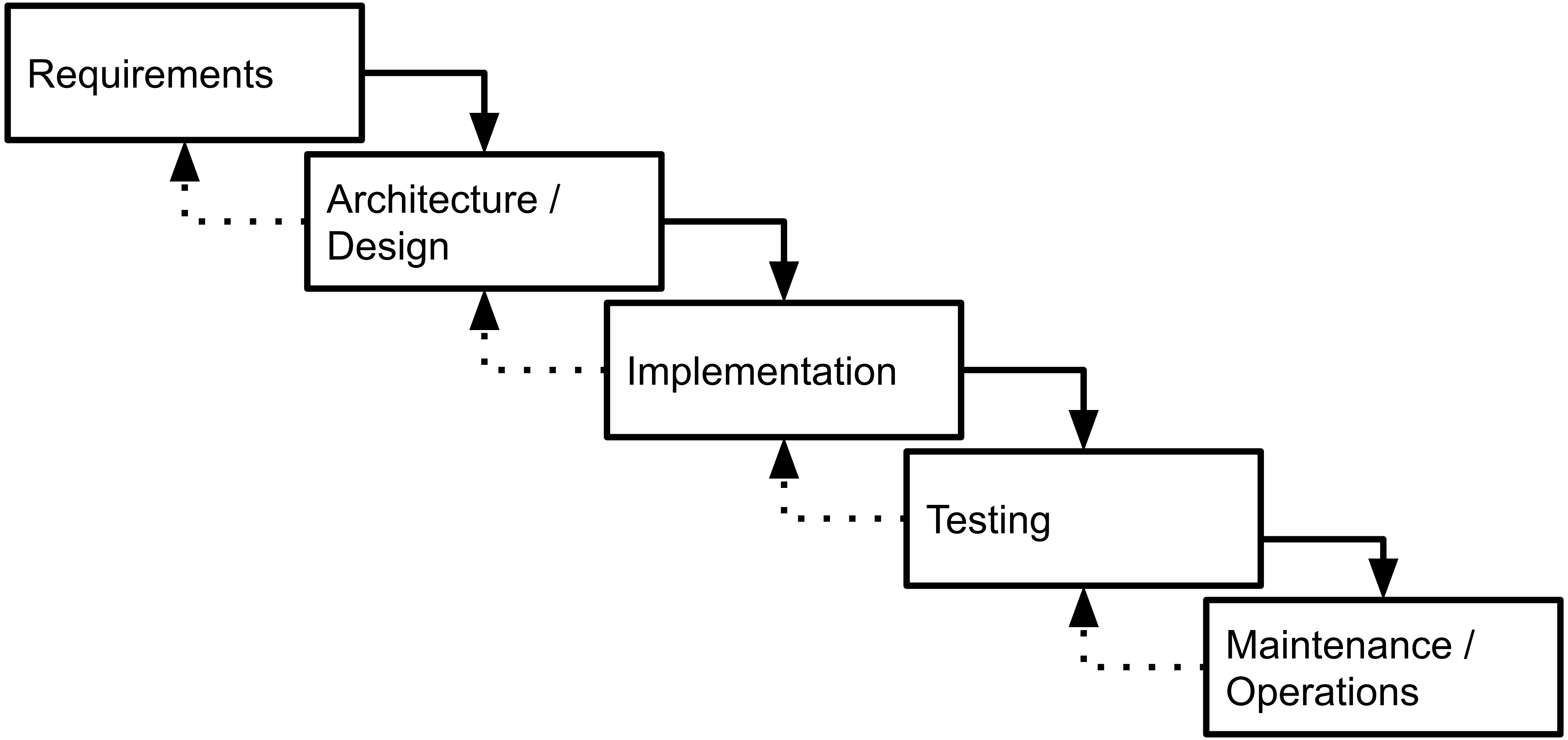
# Brief Discussion: Notebook Limitations and Drawbacks?

# Software Process Models

# Ad-hoc Processes

1. Discuss the software that needs to be written
2. Write some code
3. Test the code to identify the defects
4. Debug to find causes of defects
5. Fix the defects
6. If not done, return to step 1

# Waterfall Model



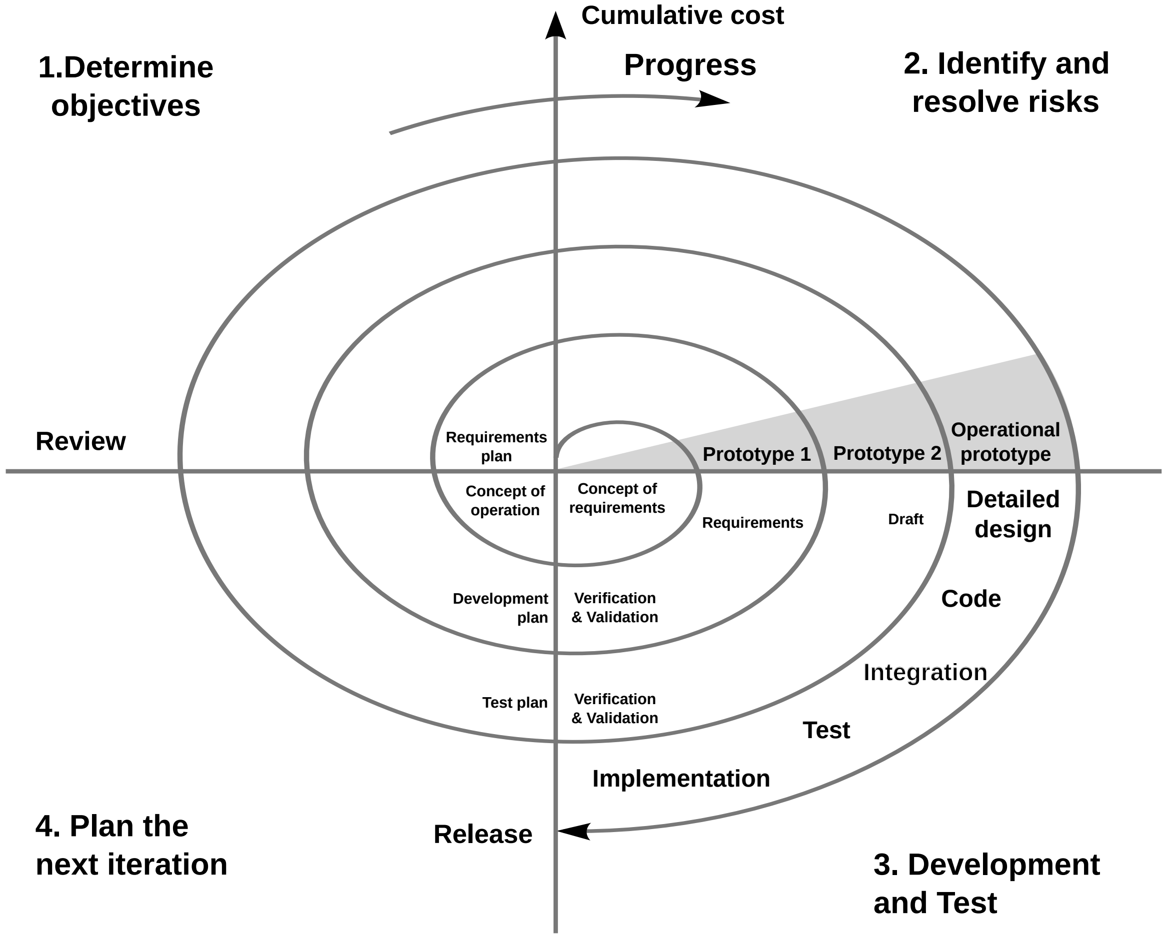

Understand requirements, plan & design before coding, test & deploy

Speaker notes

Although dated, the key idea is still essential -- think and plan before implementing. Not all requirements and design can be made upfront, but planning is usually helpful.

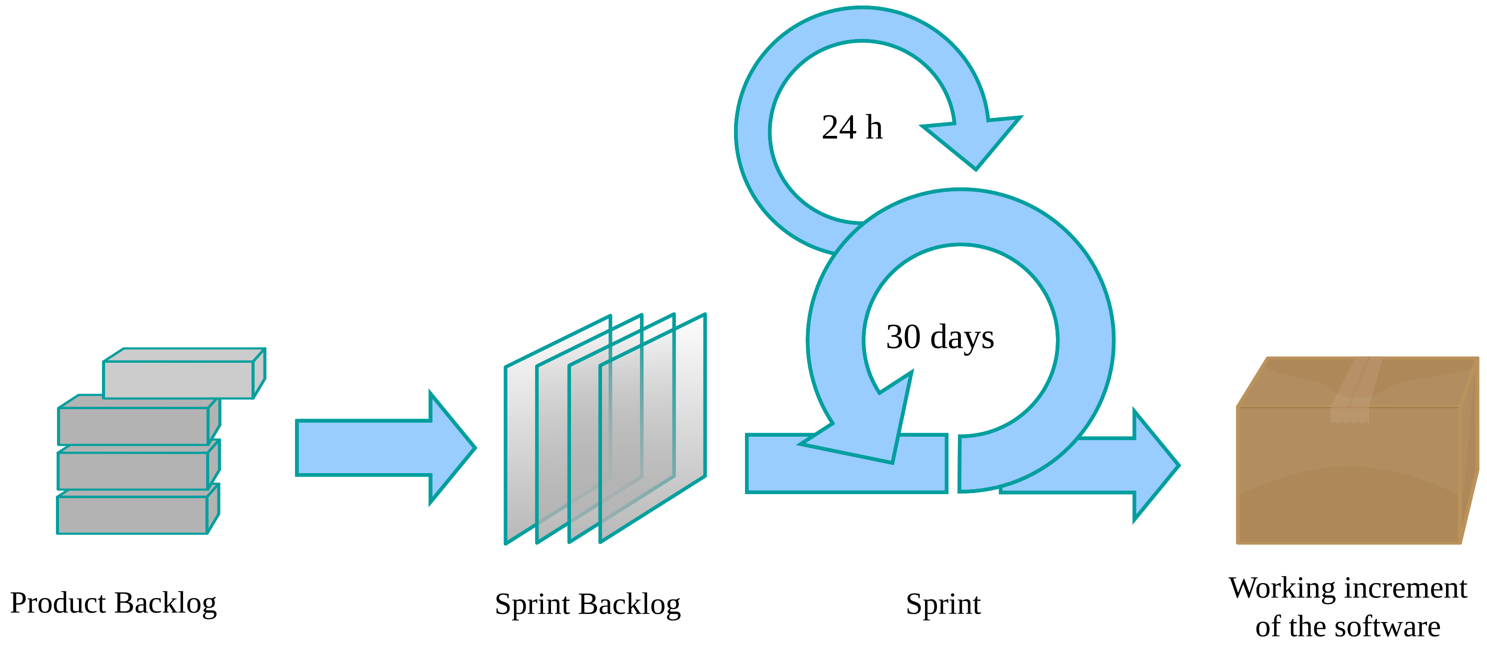
# Problems with Waterfall?

# Risk First: Spiral Model




Incremental prototypes, starting with most risky components

# Constant iteration: Agile



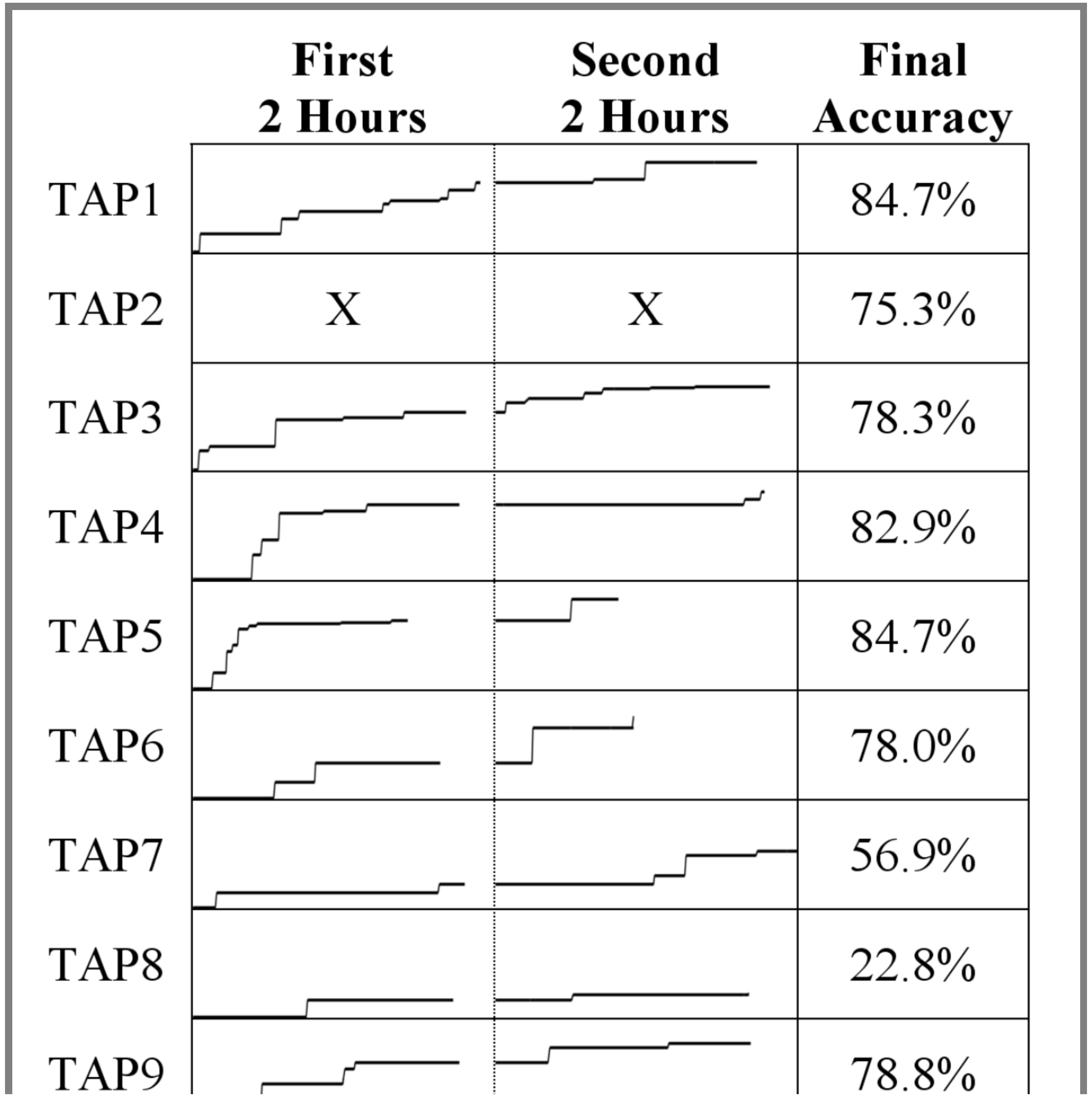

- Constant interactions with customers, constant replanning
- Scrum: Break into *sprints*; daily meetings, sprint reviews, planning

# Selecting Process Models

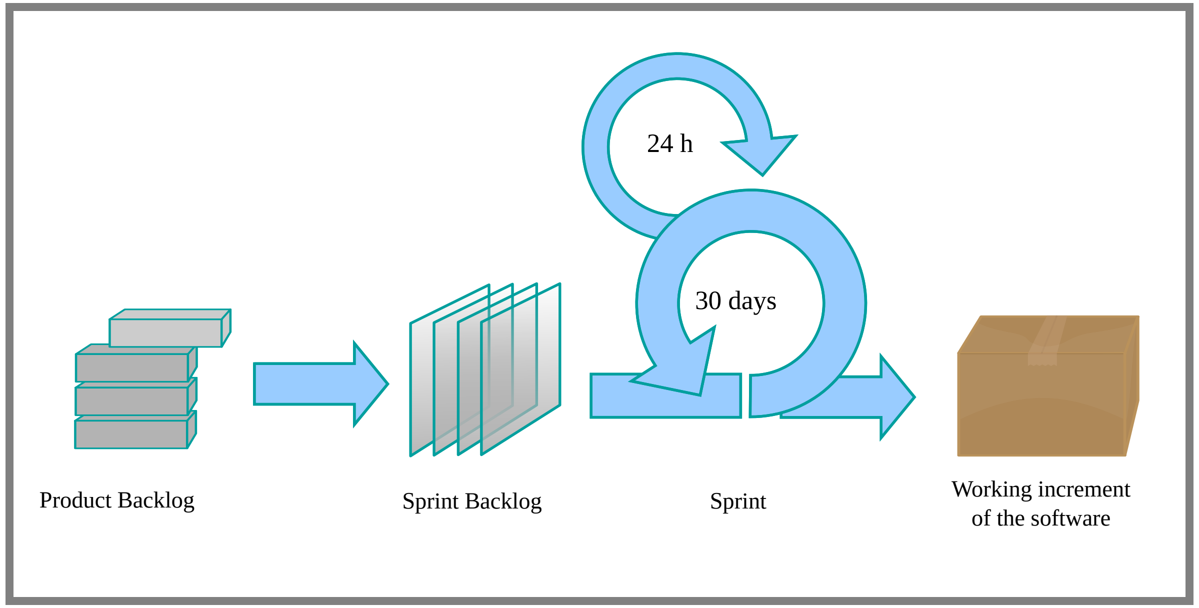
Individually, vote in `#lecture` slack: [1] Ad-hoc [2] Waterfall [3] Spiral [4] Agile

# Data Science vs Software Engineering

# Discussion: Iteration in Notebook vs Agile?



| | First 2 Hours | Second 2 Hours | Final Accuracy |
|---|---|---|---|
| TAP1 | | | 84.7% |
| TAP2 | X | X | 75.3% |
| TAP3 | | | 78.3% |
| TAP4 | | | 82.9% |
| TAP5 | | | 84.7% |
| TAP6 | | | 78.0% |
| TAP7 | | | 56.9% |
| TAP8 | | | 22.8% |
| TAP9 | | | 78.8% |



Speaker notes

There is similarity in that there is an iterative process, but the idea is different and the process model seems mostly orthogonal to iteration in data science. The spiral model prioritizes risk, especially when it is not clear whether a model is feasible. One can do similar things in model development, seeing whether it is feasible with data at hand at all and build an early prototype, but it is not clear that an initial okay model can be improved incrementally into a great one later. Agile can work with vague and changing requirements, but that again seems to be a rather orthogonal concern. Requirements on the product are not so much unclear or changing (the goal is often clear), but it's not clear whether and how a model can solve it.

# Poor Software Engineering Practices in Notebooks?

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```

- Little abstraction
- Global state
- No testing
- Heavy copy and paste
- Little documentation
- Poor version control
- Out of order execution
- Poor development features (vs IDE)

# Understanding Data Scientist Workflows

Instead of blindly recommended "SE Best Practices" understand context

Documentation and testing not a priority in exploratory phase

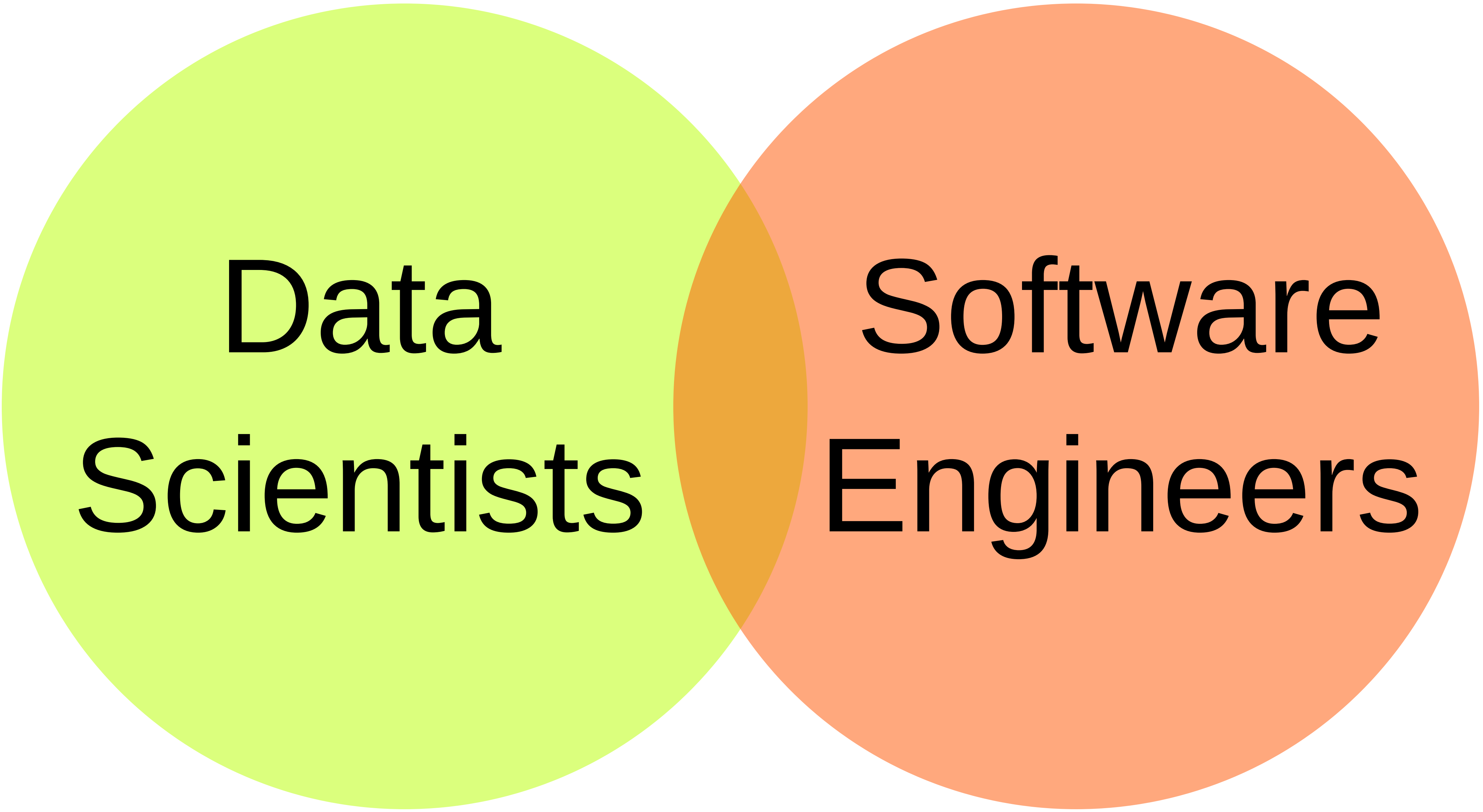
Help with transitioning into practice

- From notebooks to pipelines
- Support maintenance and iteration once deployed
- Provide infrastructure and tools

# Data Science Practices by Software Eng.

- Many software engineers get involved in data science without explicit training
- Copying from public examples, little reading of documentation
- Lack of data visualization/exploration/understanding, no focus on data quality
- Strong preference for code editors, non-GUI tools
- Improve model by adding more data or changing models, rarely feature engineering or debugging
- Lack of awareness about overfitting/bias problems, single focus on accuracy, no monitoring
- More system thinking about the product and its needs

Yang, Qian, Jina Suh, Nan-Chen Chen, and Gonzalo Ramos. "Grounding interactive machine learning tool design in how non-experts actually build models." In *Proceedings of the 2018 Designing Interactive Systems Conference*, pp. 573-584. 2018.


Data
Scientists
Software
Engineers

# Integrated Process for AI-Enabled Systems

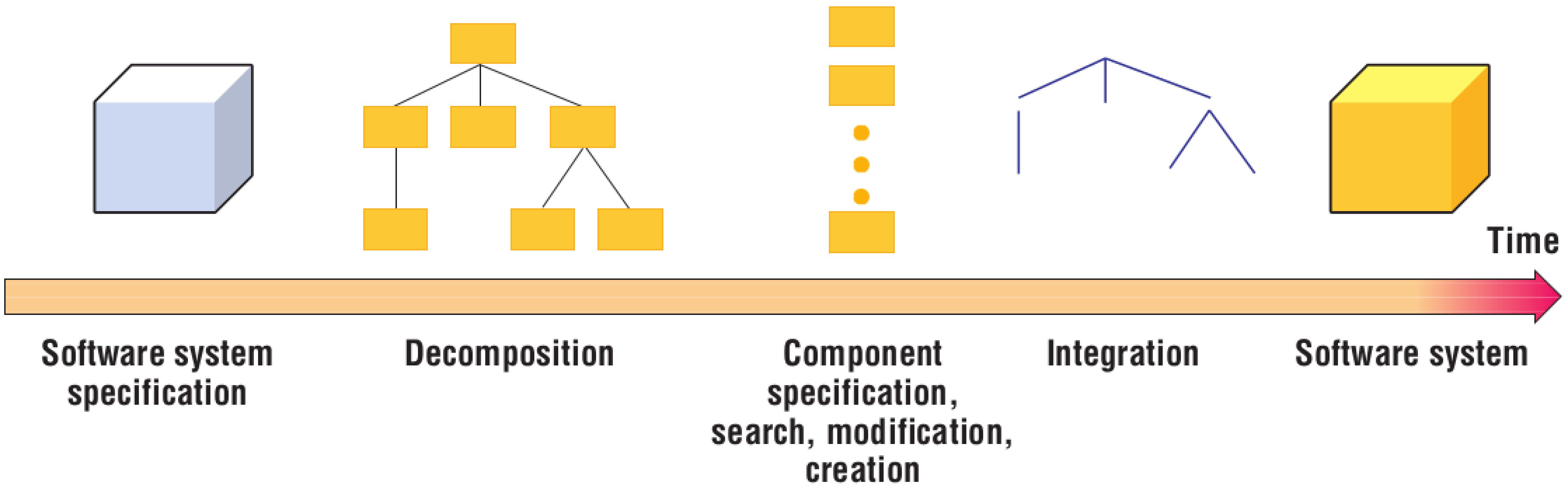
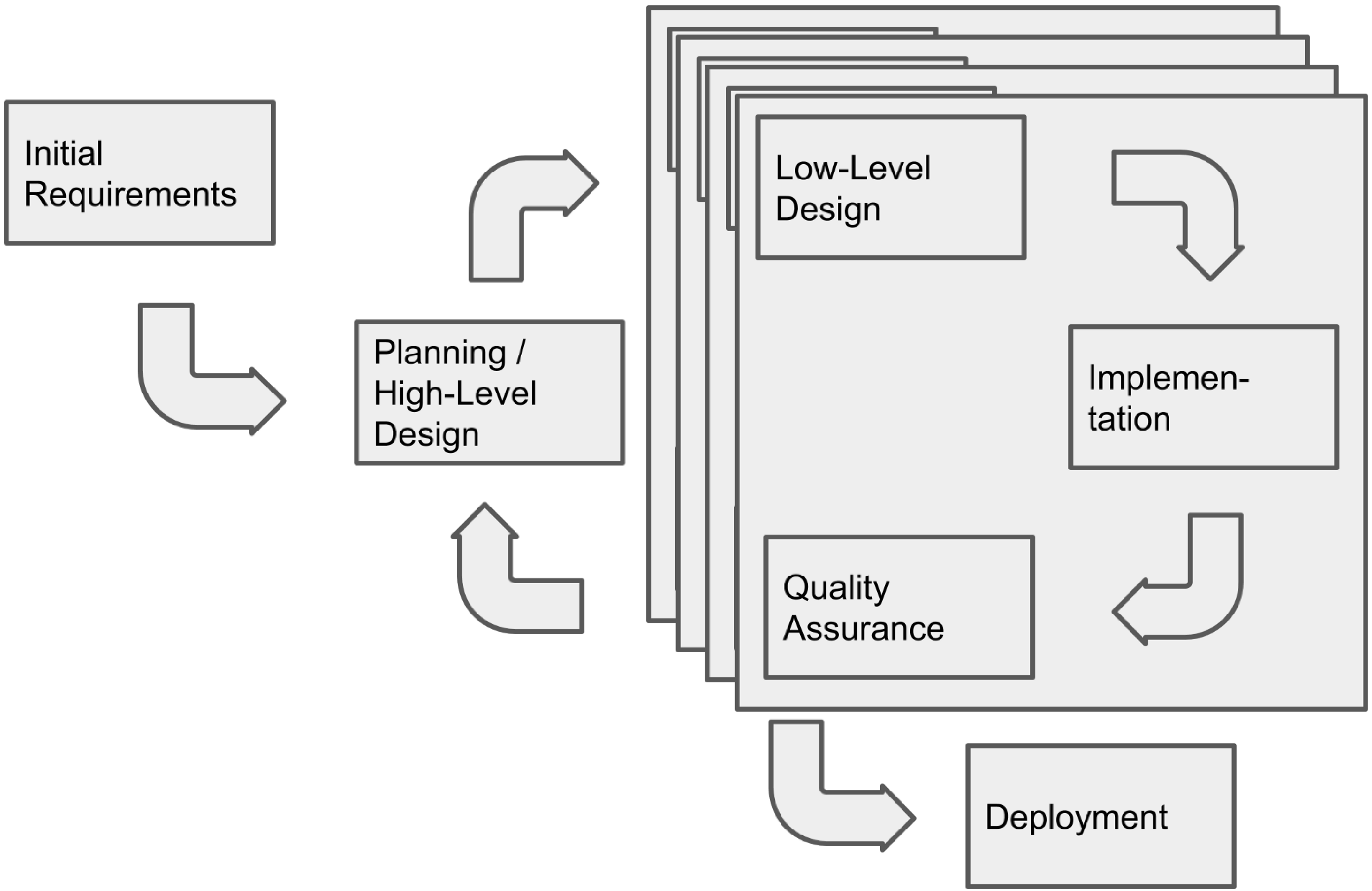
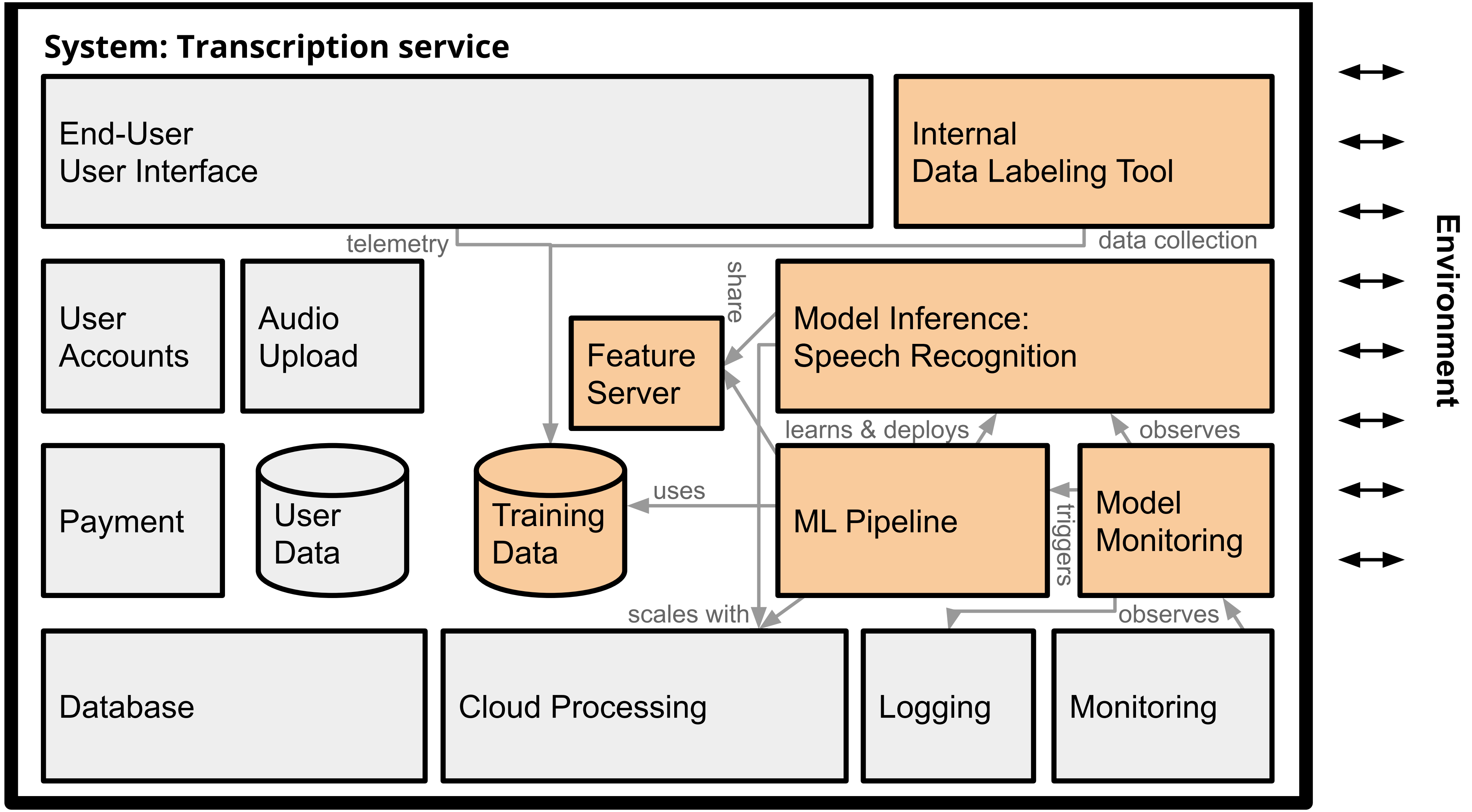


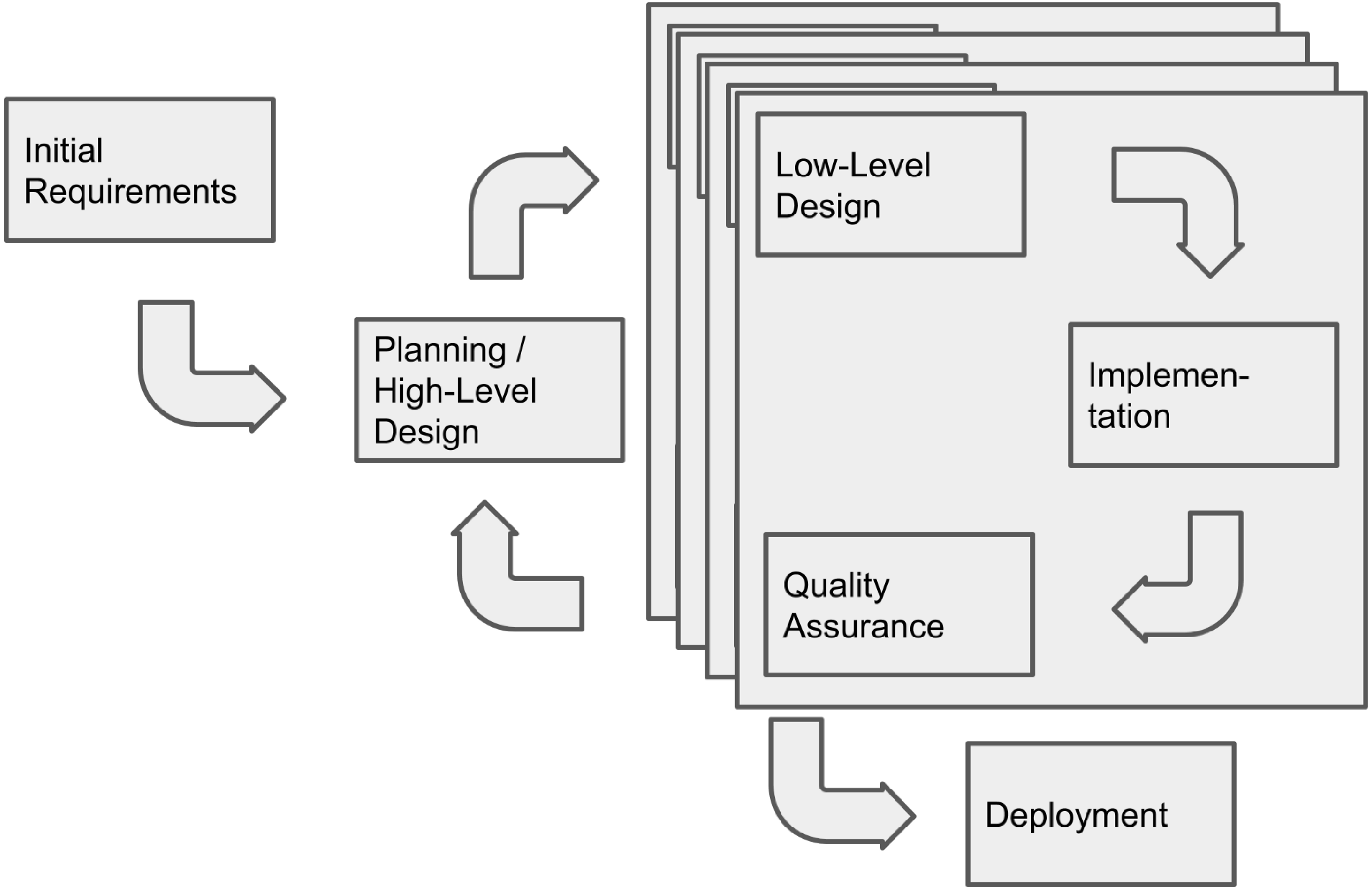

Figure from Dogru, Ali H., and Murat M. Tanik. “A process model for component-oriented software engineering.” IEEE Software 20, no. 2 (2003): 34–41.


Initial Requirements
Planning / High-Level Design
Low-Level Design
Implemen-tation
Quality Assurance
Deployment

# Recall: ML models are system components




Legend: Non-ML component, ML component, system boundary



Initial Requirements
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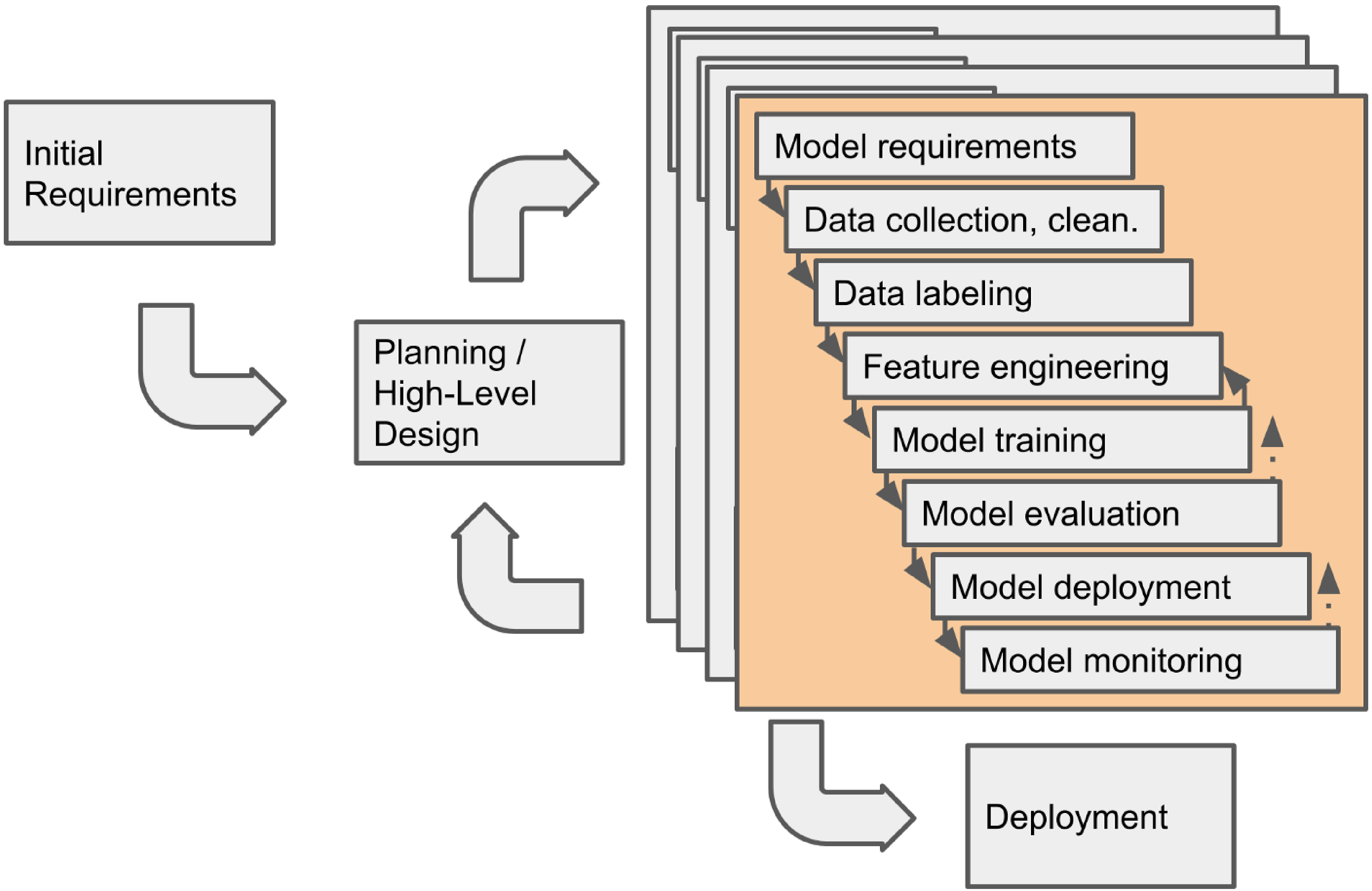
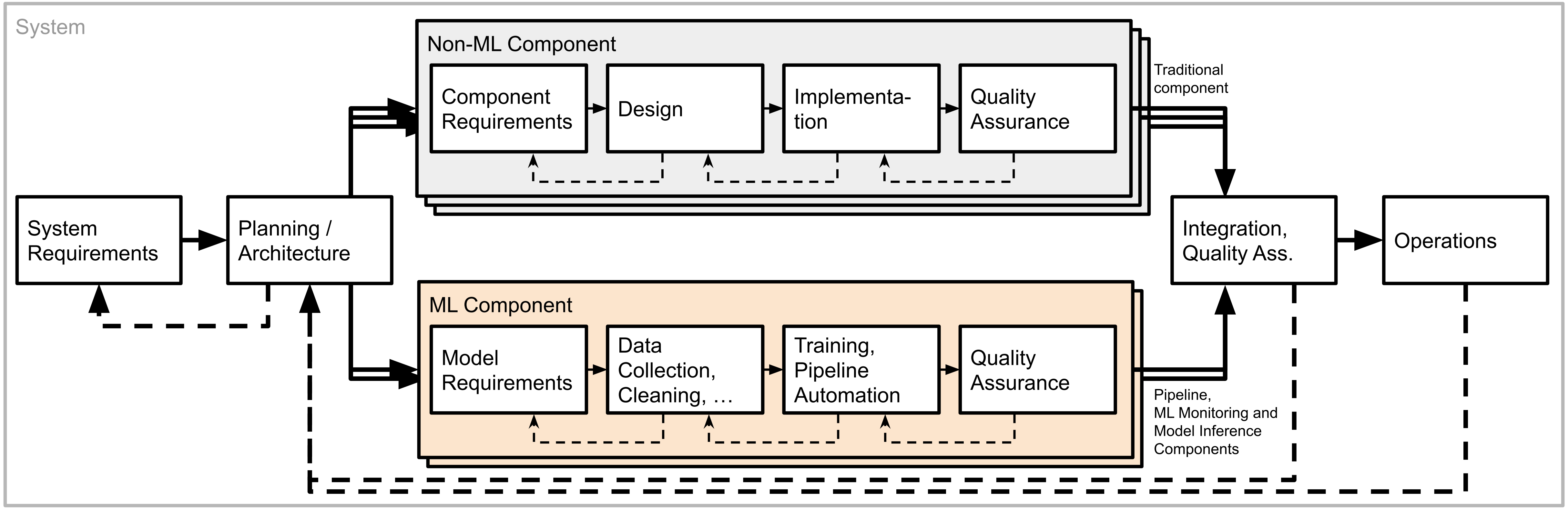

Initial Requirements
Planning / High-Level Design
Model requirements
Data collection, clean.
Data labeling
Feature engineering
Model training
Model evaluation
Model deployment
Model monitoring
Deployment


System
Non-ML Component
Component Requirements
Design
Implementa-tion
Quality Assurance
Traditional component
System Requirements
Planning / Architecture
Integration, Quality Ass.
Operations
ML Component
Model Requirements
Data Collection, Cleaning, …
Training, Pipeline Automation
Quality Assurance
Pipeline, ML Monitoring and Model Inference Components

# Process for AI-Enabled Systems

- Integrate Software Engineering and Data Science processes
- Establish system-level requirements (e.g., user needs, safety, fairness)
- Inform data science modeling with system requirements (e.g., privacy, fairness)
- Try risky parts first (most likely include ML components; ~spiral)
- Incrementally develop prototypes, incorporate user feedback (~agile)
- Provide flexibility to iterate and improve
- Design system with characteristics of AI component (e.g., UI design, safeguards)
- Plan for testing throughout the process and in production
- Manage project understanding both software engineering and data science workflows

- **No existing "best practices" or workflow models**

# Trajectories

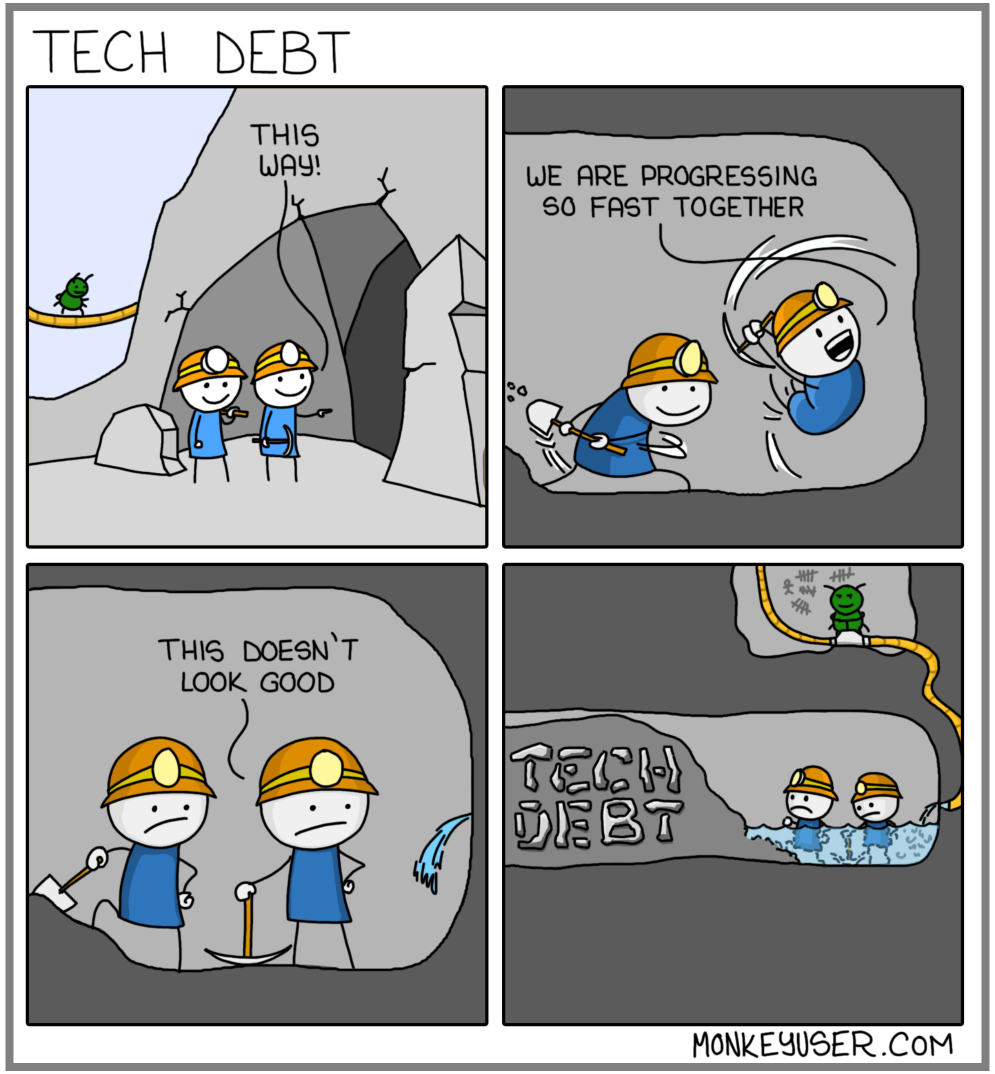
Not every project follows the same development process, e.g.

- Small ML addition: Product first, add ML feature later
- Research only: Explore feasibility before thinking about a product
- Data science first: Model as central component of potential product, build system around it

Different focus on system requirements, qualities, and upfront planning

Manage interdisciplinary teams and different expectations

# Technical debt



# Technical Debt Metaphor

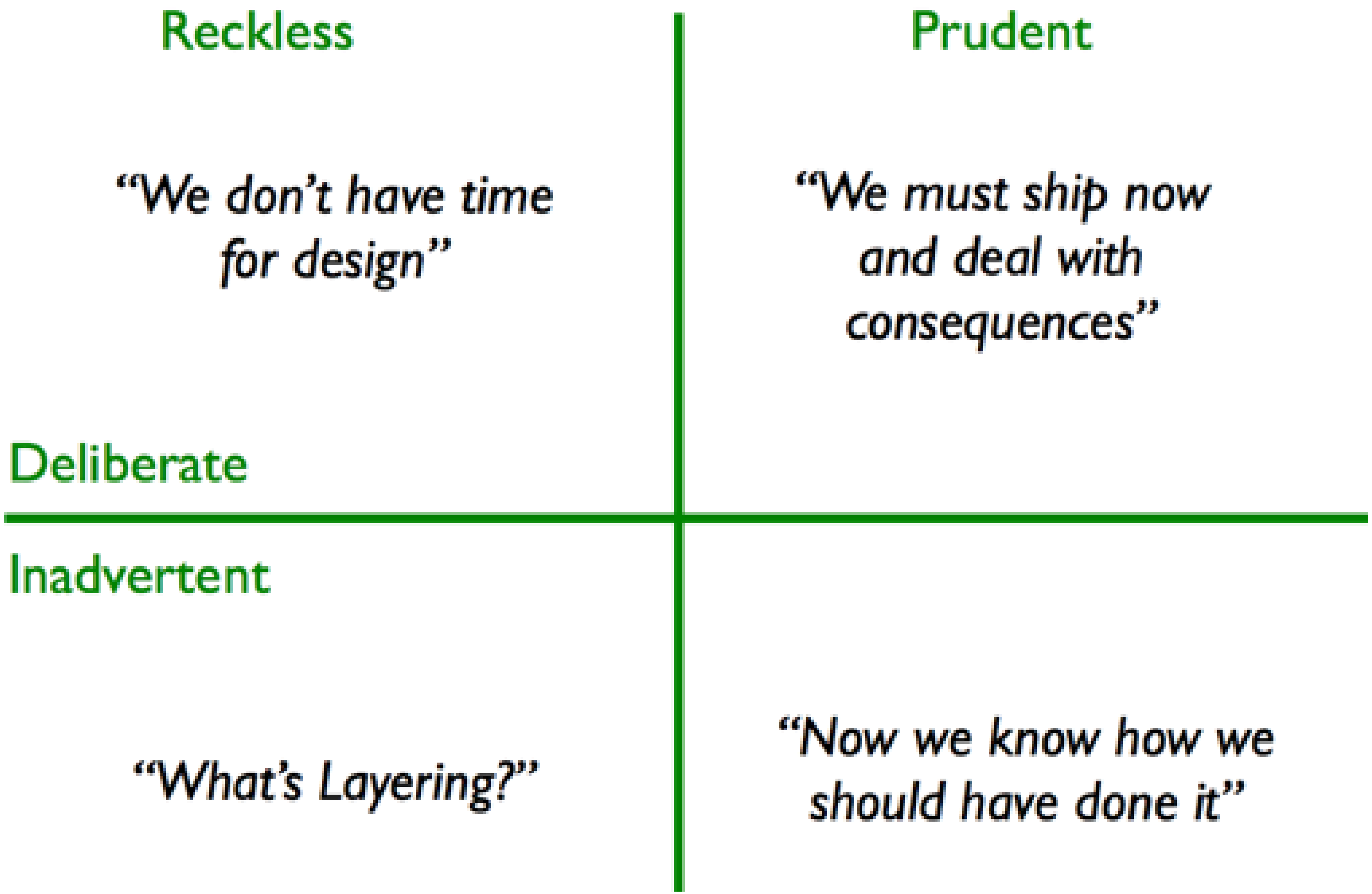
Analogy to financial debt

- Make a decision for an immediate benefit (e.g., release now)
- Accepting later cost (loss of productivity, higher maintenance and operating cost, rework)
- Debt accumulates and can suffocate project

Ideally, a deliberate decision (short term tactical or long term strategic)

Ideally, track debt and plan for paying it down later

**Q. Examples?**




Source: Martin Fowler 2009, https://martinfowler.com/bliki/TechnicalDebtQuadrant.html

| | **Reckless** | **Prudent** |
|---|---|---|
| **Deliberate** | *“We don’t have time to plan for mistakes.”* | *“We must release now before the competition and deal with slow manual releases for now.”* |
| **Inadvertent** | *“What’s data drift?”* | *“We didn’t know about data versioning and in retrospect it’s good we didn’t waste a lot of effort on it early on.”* |

# Technical Debt: Examples

Prudent & deliberate: Skip using a CI platform

- Reason for debt: Short deadline; test the product viability with alpha users using a prototype
- Debt payback: Refactoring effort to integrate the system into CI

Reckless & inadvertent: Forget to encrypt user credentials in DB

- Reason for debt: Lack of in-house security expertise
- Debt payback: Security vulnerabilities & fallouts from an attack (loss of data); effort to retrofit security into the system

# Breakout: Technical Debt from ML

As a group in `#lecture`, tagging members: Post two plausible examples technical debt in housing price prediction system:

1. Deliberate, prudent:
2. Reckless, inadvertent:

# Technical Debt through Notebooks?

> *Jupyter Notebooks are a gift from God to those who work with data. They allow us to do quick experiments with Julia, Python, R, and more -- John Paul Ada*

Speaker notes

Discuss benefits and drawbacks of Jupyter style notebooks

# ML and Technical Debt

**Often reckless and inadvertent in inexperienced teams**

ML can seem like an easy addition, but it may cause long-term costs

Needs to be maintained, evolved, and debugged

Goals may change, environment may change, some changes are subtle

# Example problems: ML and Technical Debt

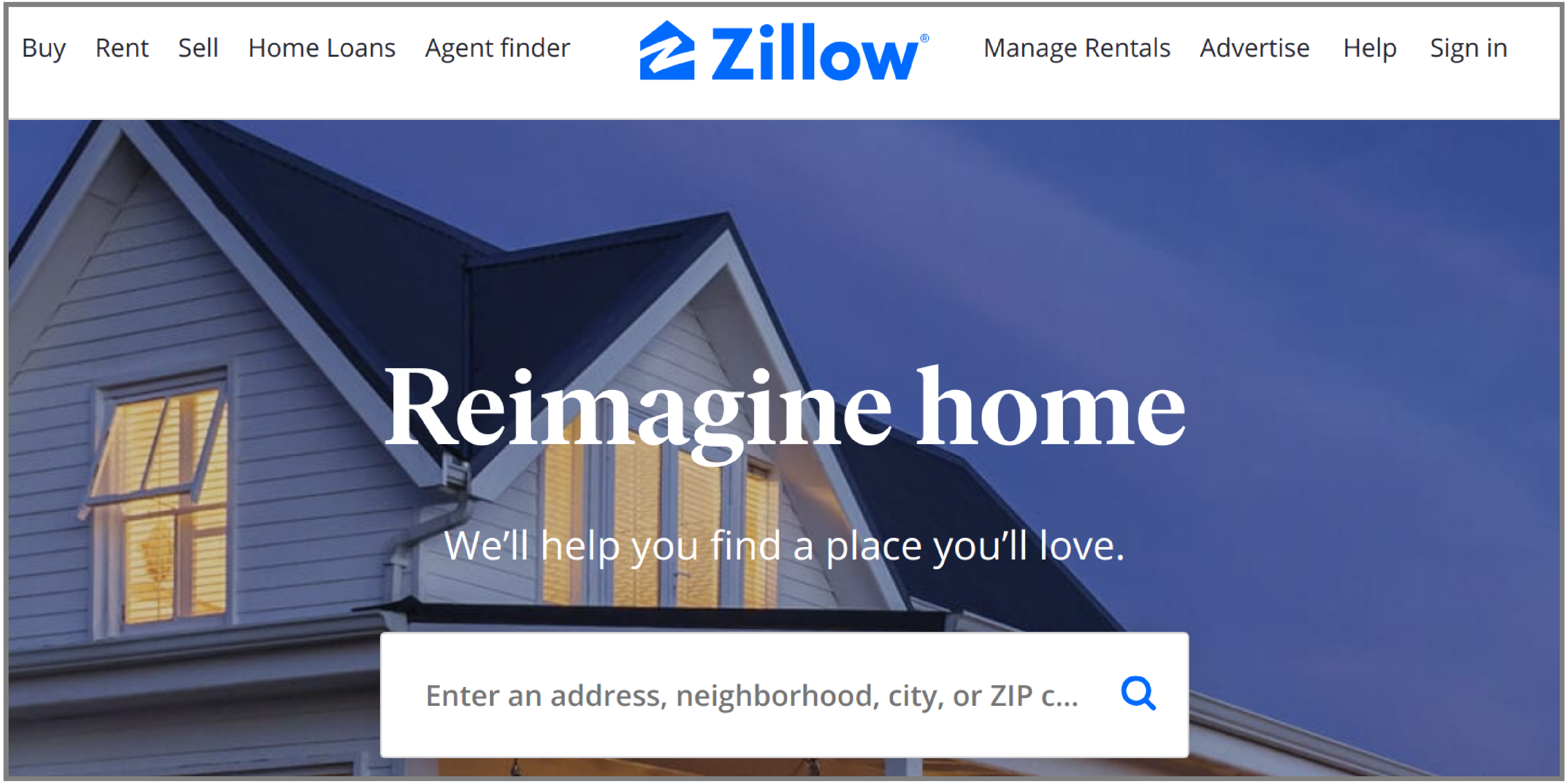
- Systems and models are tangled and changing one has cascading effects on the other
- Untested, brittle infrastructure; manual deployment
- Unstable data dependencies, replication crisis
- Data drift and feedback loops
- Magic constants and dead experimental code paths

Further reading: Sculley, David, et al. Hidden technical debt in machine learning systems. Advances in Neural Information Processing Systems. 2015.

# Controlling Technical Debt from ML Components

# Controlling Technical Debt from ML Components

- Avoid AI when not needed
- Understand and document requirements, design for mistakes
- Build reliable and maintainable pipelines, infrastructure, good engineering practices
- Test infrastructure, system testing, testing and monitoring in production
- Test and monitor data quality
- Understand and model data dependencies, feedback loops, ...
- Document design intent and system architecture
- Strong interdisciplinary teams with joint responsibilities
- Document and track technical debt
- ...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# Summary

Data scientists and software engineers follow different processes

ML projects need to consider process needs of both

Iteration and upfront planning are both important, process models codify good practices

Deliberate technical debt can be good, too much debt can suffocate a project

Easy to amount (reckless) technical debt with machine learning

# Further Reading


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- Yang, Qian, Jina Suh, Nan-Chen Chen, and Gonzalo Ramos. "Grounding interactive machine learning tool design in how non-experts actually build models." In *Proceedings of the 2018 Designing Interactive Systems Conference*, pp. 573-584. 2018.
- Fowler and Highsmith. The Agile Manifesto
- Steve McConnell. Software project survival guide. Chapter 3
- Pfleeger and Atlee. Software Engineering: Theory and Practice. Chapter 2
- Kruchten, Philippe, Robert L. Nord, and Ipek Ozkaya. "Technical debt: From metaphor to theory and practice." IEEE Software 29, no. 6 (2012): 18-21.