

PROCESS AND TECHNICAL DEBT

Christian Kaestner

Required Reading:

- Sculley, David, Gary Holt, Daniel Golovin, Eugene Davydov, Todd Phillips, Dietmar Ebner, Vinay Chaudhary, Michael Young, Jean-Francois Crespo, and Dan Dennison. "[Hidden technical debt in machine learning systems](#)." In Advances in neural information processing systems, pp. 2503-2511. 2015.

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

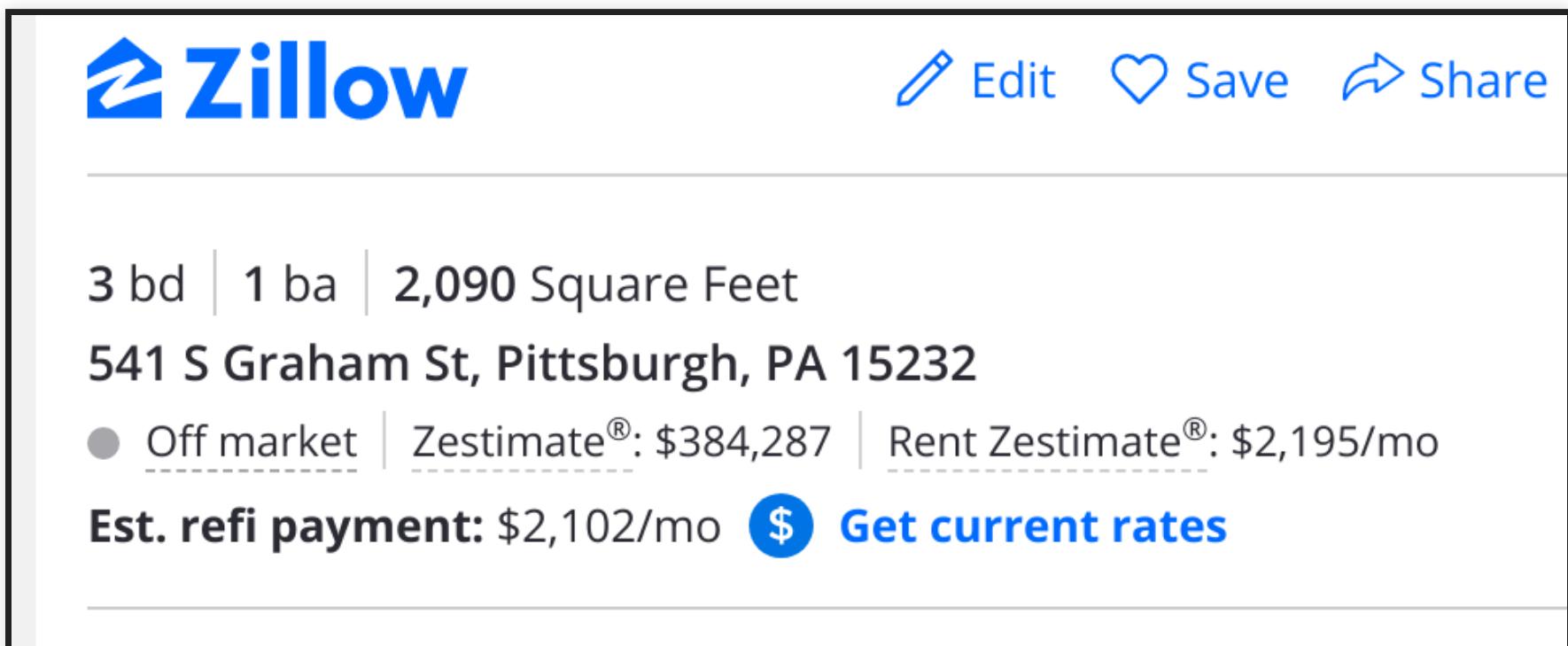
CASE STUDY: REAL-ESTATE WEBSITE

The image shows the Zillow website homepage. At the top, there is a navigation bar with links for "Buy", "Rent", "Sell", "Home Loans", "Agent finder", "Manage Rentals", "Advertise", "Help", and "Sign in". The Zillow logo, consisting of a blue stylized 'z' icon followed by the word "Zillow" in a bold, sans-serif font, is prominently displayed. Below the navigation bar is a large, dark blue background image of a two-story house with white horizontal siding and a dark roof. Overlaid on this image is the text "Reimagine home" in a large, white, serif font. Below this, a smaller white text box contains the slogan "We'll help you find a place you'll love." At the bottom of the page, there is a white search bar with the placeholder text "Enter an address, neighborhood, city, or ZIP c..." followed by a blue magnifying glass icon.

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.

$$f(\text{size}, \text{rooms}, \text{tax}, \text{neighborhood}, \dots) \rightarrow \text{price}$$



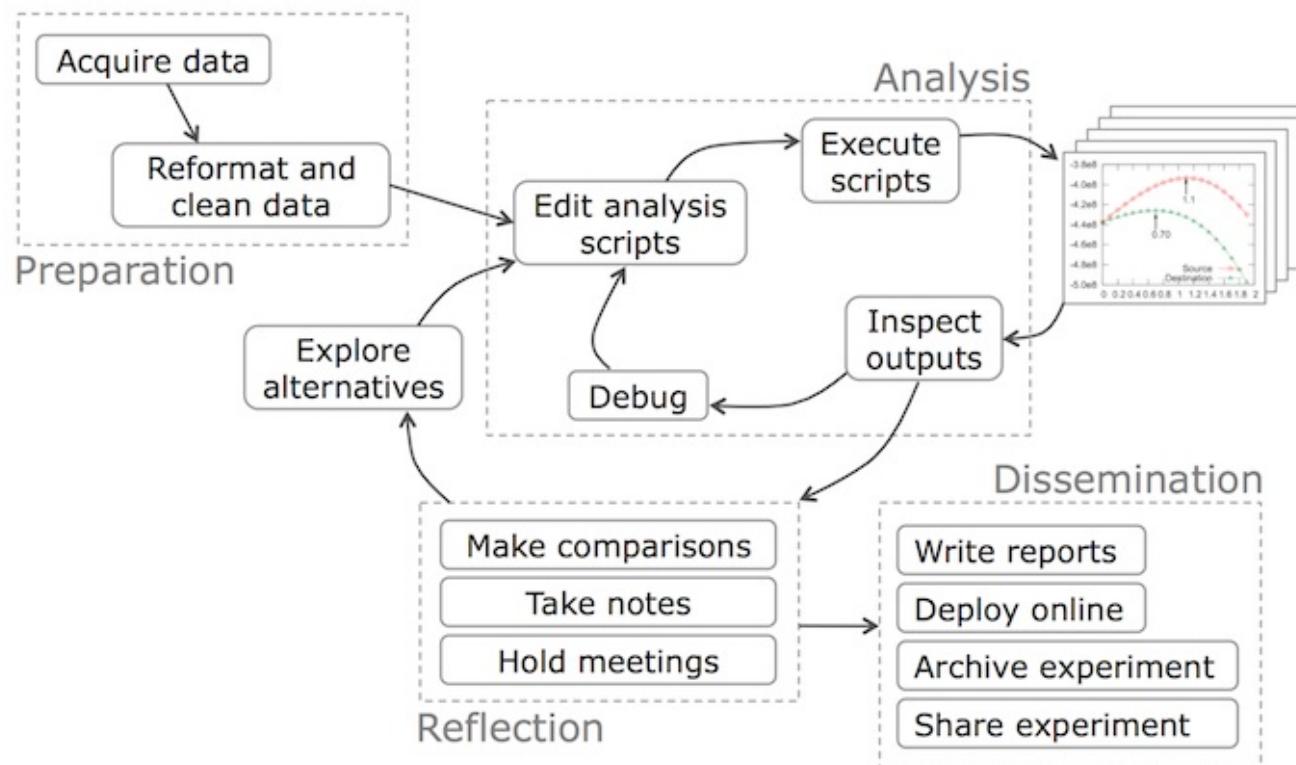
A screenshot of a Zillow real estate listing page. The top navigation bar includes the Zillow logo, a pencil icon for Edit, a heart icon for Save, and a share icon. Below the header, the listing details are shown: "3 bd | 1 ba | 2,090 Square Feet" and the address "541 S Graham St, Pittsburgh, PA 15232". A status indicator shows the property is "Off market". Zestimate information is provided: "Zestimate®: \$384,287" and "Rent Zestimate®: \$2,195/mo". At the bottom, there is a callout for "Est. refi payment: \$2,102/mo" followed by a dollar sign icon and a blue button labeled "Get current rates".

DATA SCIENCE: ITERATION AND EXPLORATION

WHAT'S YOUR PROCESS?



DATA SCIENCE IS ITERATIVE AND EXPLORATORY



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

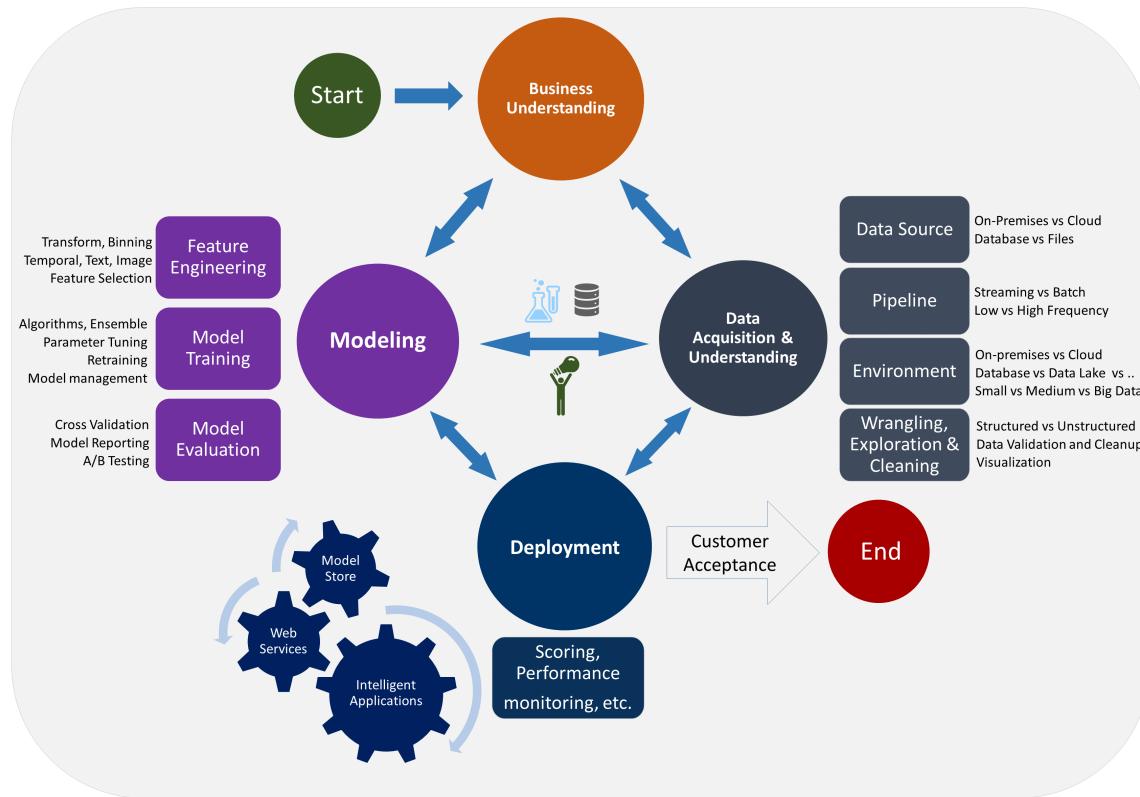
DATA SCIENCE IS ITERATIVE AND EXPLORATORY



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).

DATA SCIENCE IS ITERATIVE AND EXPLORATORY

Data Science Lifecycle



(Microsoft Azure Team, "What is the Team Data Science Process?" Microsoft Documentation, 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.

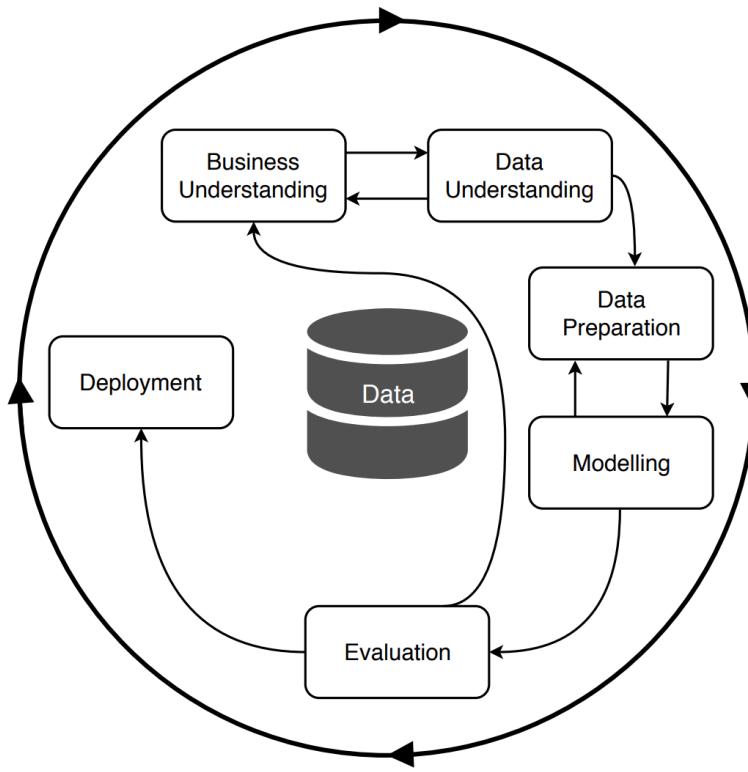
DATA SCIENCE IS ITERATIVE AND EXPLORATORY

- 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



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).

DIFFERENT TRAJECTORIES



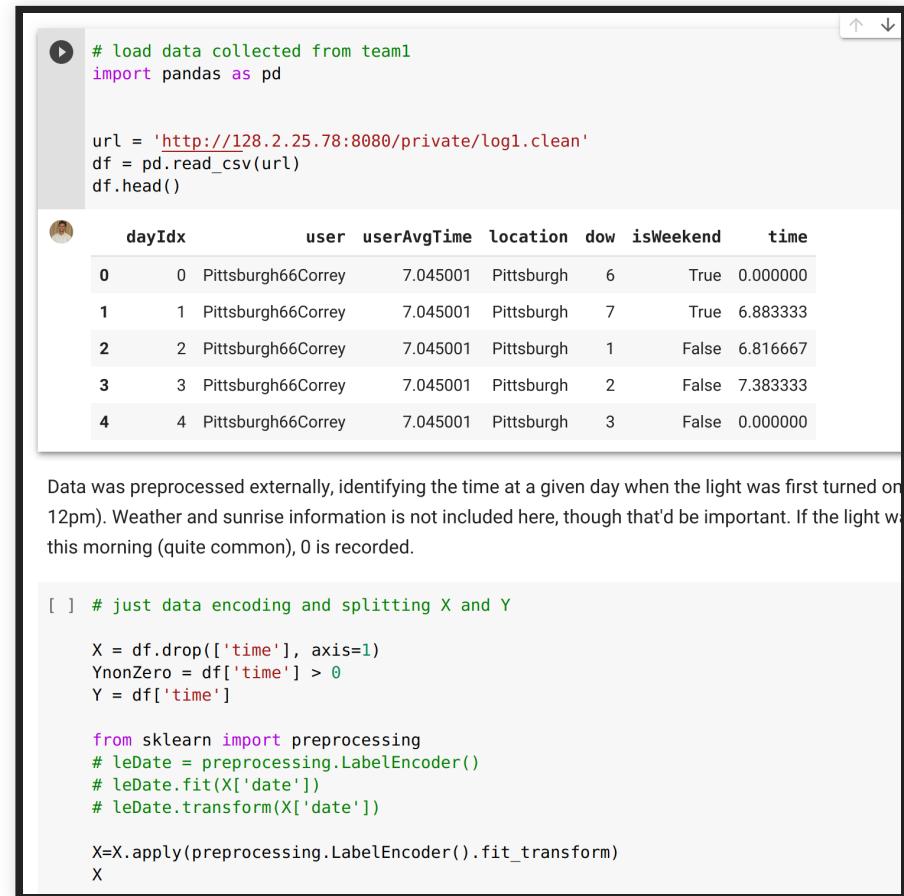
From: Martínez-Plumed et al. "[CRISP-DM Twenty Years Later: From Data Mining Processes to Data Science Trajectories](#)." IEEE Transactions on Knowledge and Data Engineering (2019).

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



A screenshot of a Jupyter Notebook cell. The cell contains the following code:

```
# 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()
```

The output of the cell is a Pandas DataFrame:

dayIdx	user	userAvgTime	location	dow	isWeekend	time
0	Pittsburgh66Correy	7.045001	Pittsburgh	6	True	0.000000
1	Pittsburgh66Correy	7.045001	Pittsburgh	7	True	6.883333
2	Pittsburgh66Correy	7.045001	Pittsburgh	1	False	6.816667
3	Pittsburgh66Correy	7.045001	Pittsburgh	2	False	7.383333
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 was turned on 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 ENGINEERING PROCESS

INNOVATIVE VS ROUTINE PROJECTS

- Like data science tasks, most software projects are innovative
 - Google, Amazon, Ebay, Netflix
 - Vehicles and robotics
 - Language processing, Graphics, AI
- Routine (now, not 20 years ago)
 - E-commerce websites?
 - Product recommendation? Voice recognition?
 - Routine gets automated -> innovation cycle

A SIMPLE PROCESS

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

SOFTWARE PROCESS

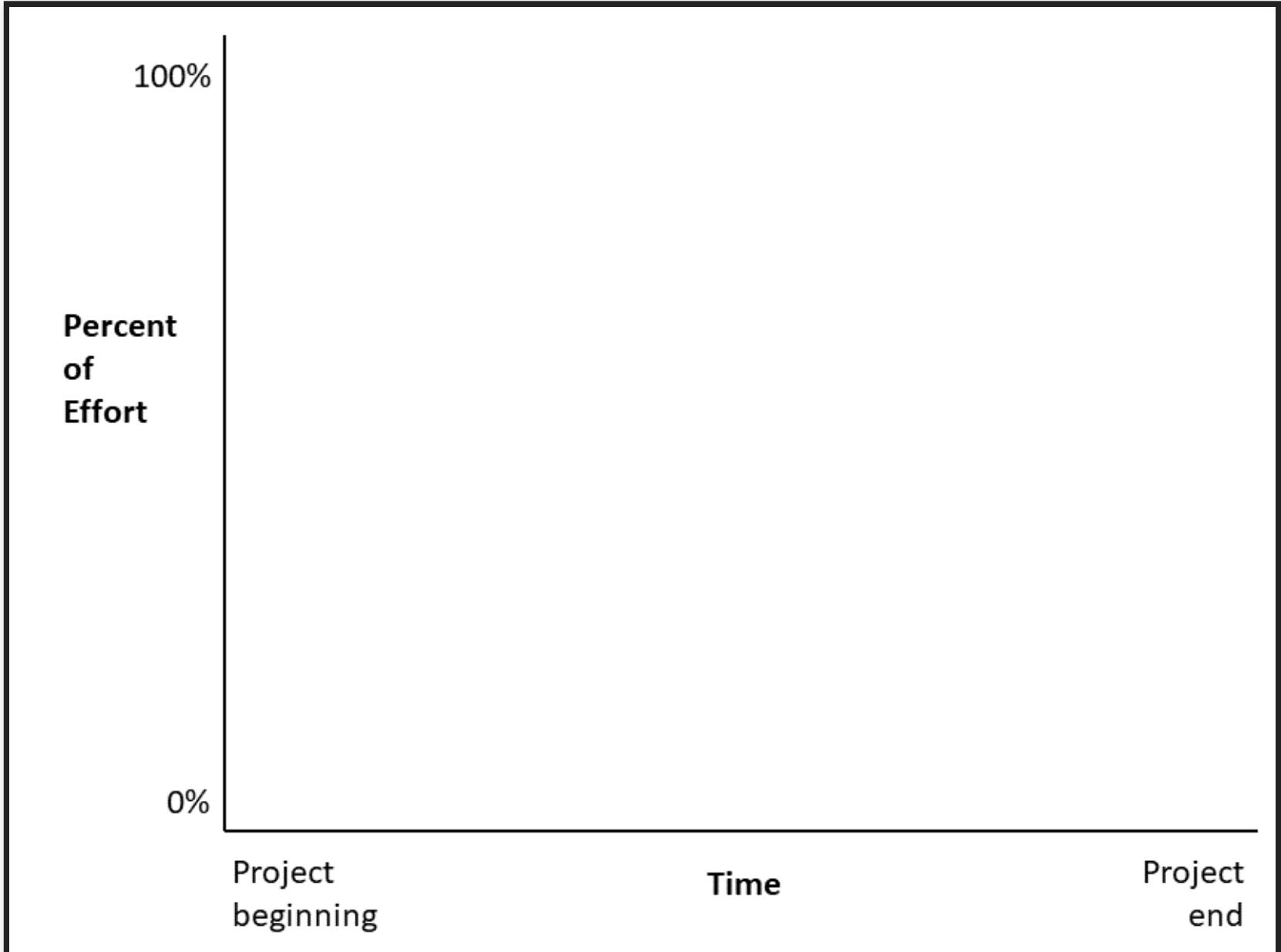
“The set of activities and associated results that produce a software product”

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



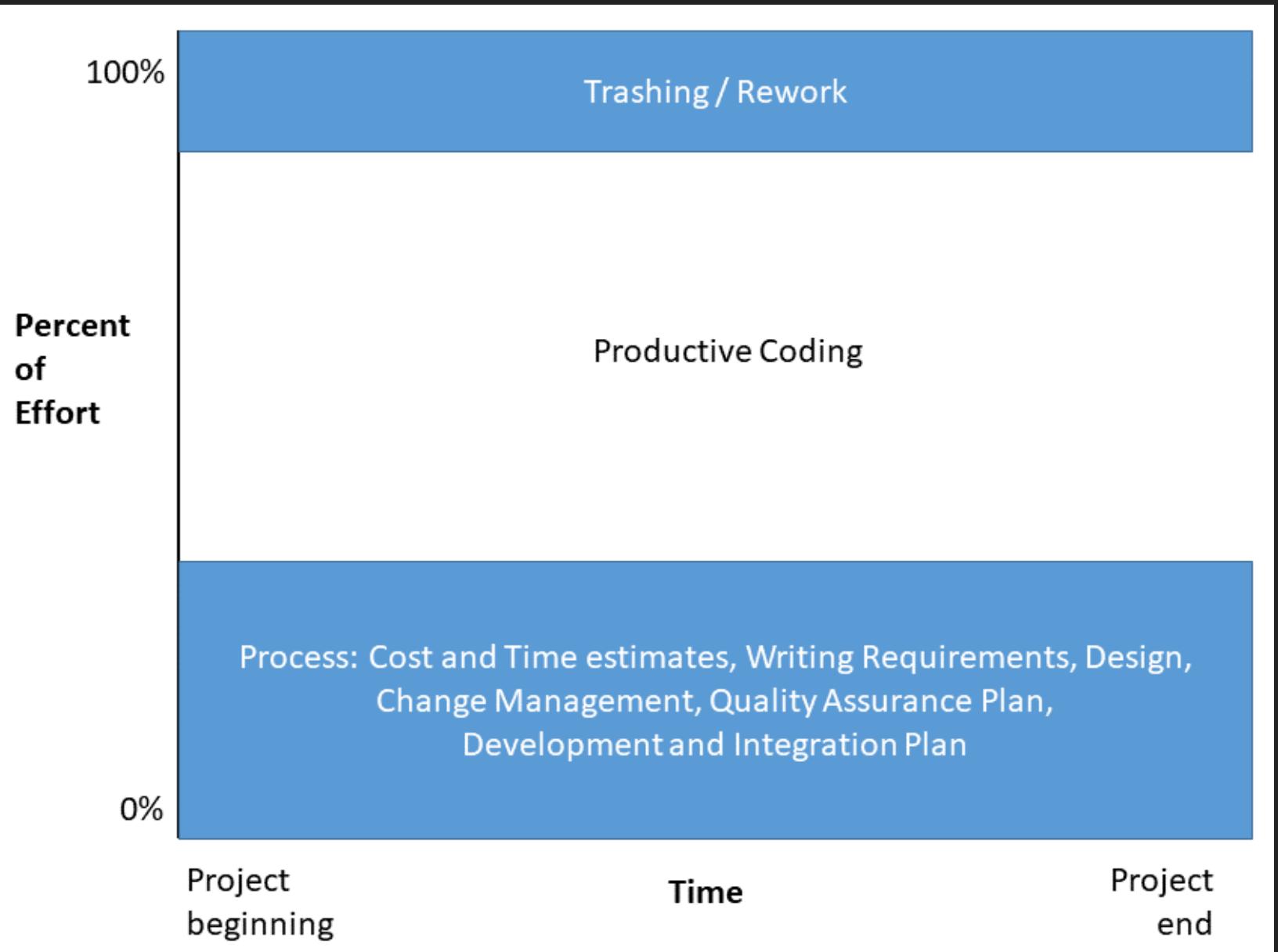
Speaker notes

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



Speaker notes

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



Speaker notes

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



Speaker notes

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

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.

TYPICAL PROCESS STEPS (NOT NECESSARILY IN THIS ORDER)

- Understand customers, identify what to build, by when, budget
- Identify relevant qualities, plan/design system accordingly
- Test, deploy, maintain, evolve
- Plan, staff, workaround

Buy Rent Sell Home Loans Agent finder



Manage Rentals Advertise Help Sign in



Reimagine home

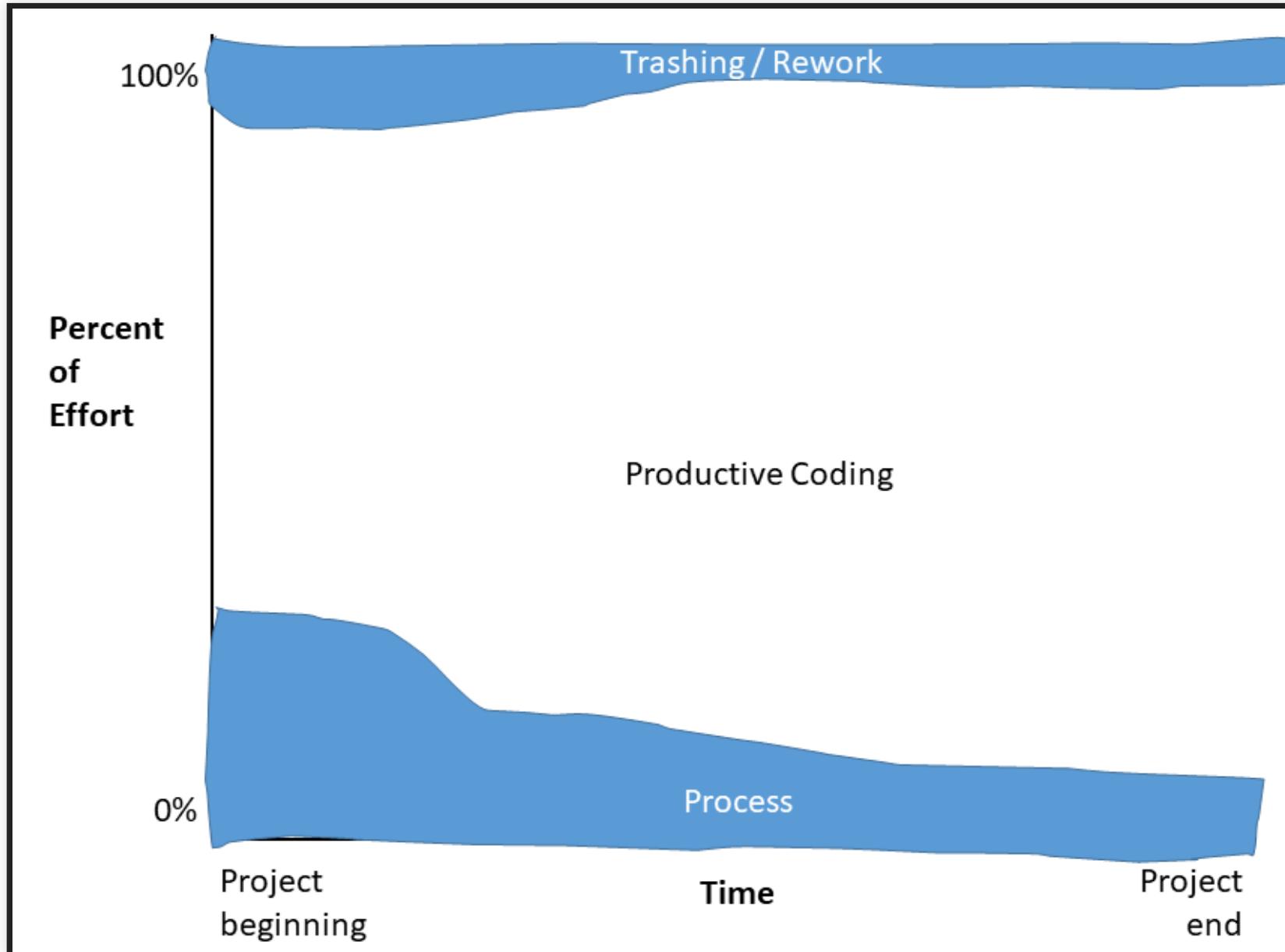
We'll help you find a place you'll love.

Enter an address, neighborhood, city, or ZIP c... 

SURVIVAL MODE

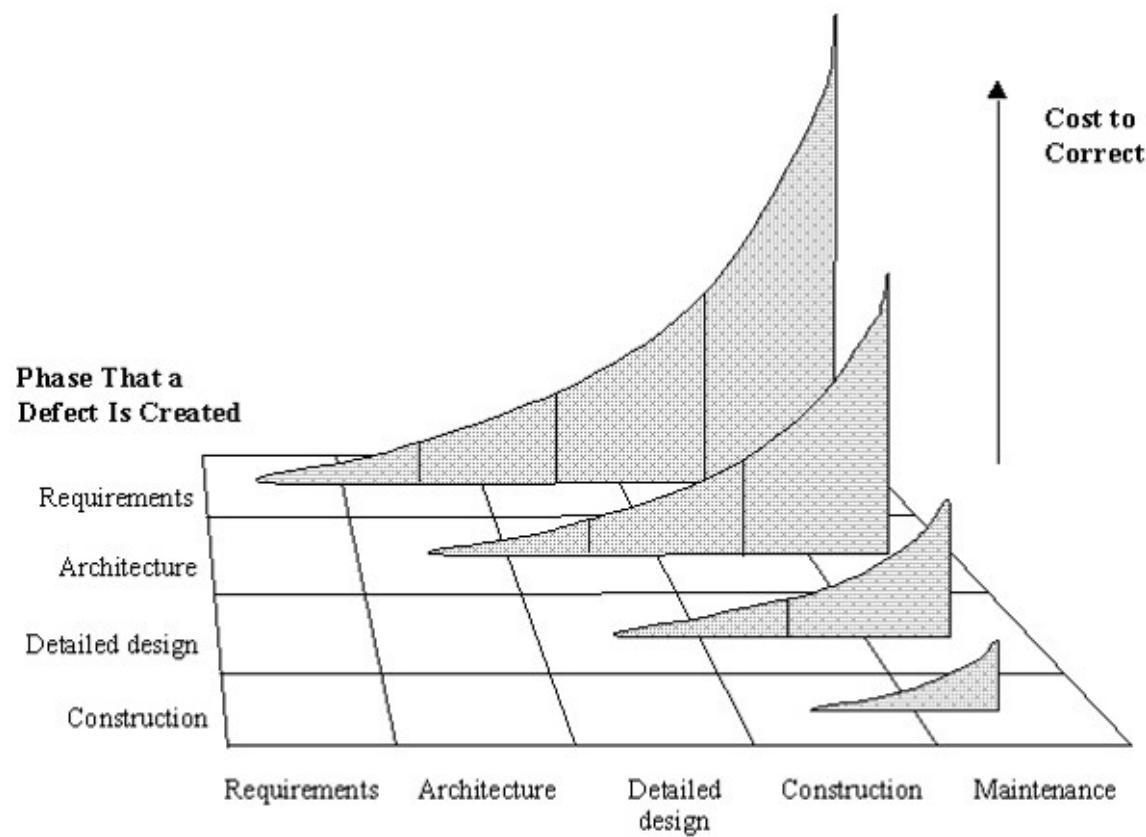
- Missed deadlines -> "solo development mode" to meet own deadlines
- Ignore integration work
- Stop interacting with testers, technical writers, managers, ...

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



Speaker notes

ideal setting of little process investment upfront



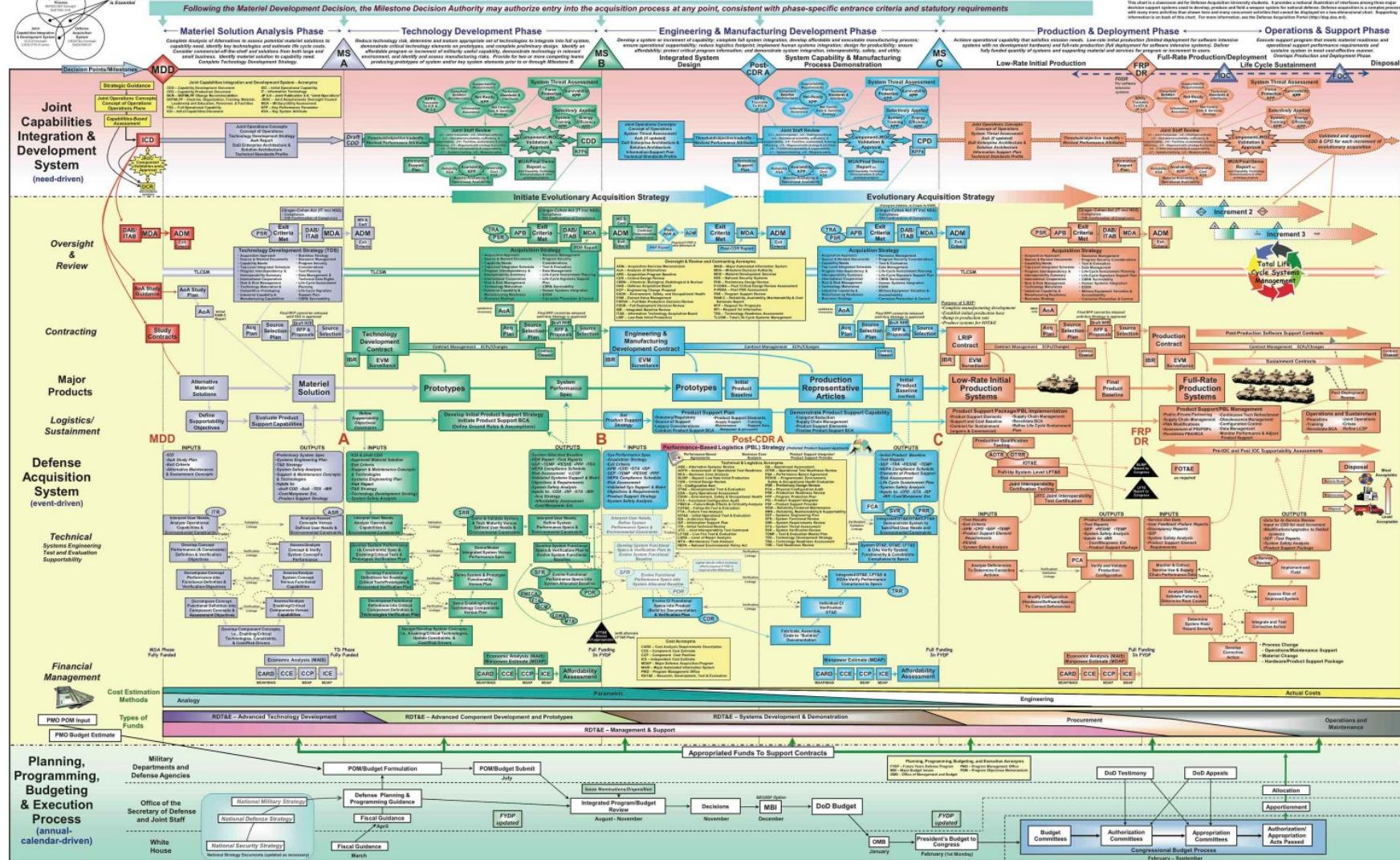
Phase That a Defect Is Corrected

Copyright 1998 Steven C. McConnell. Reprinted with permission from *Software Project Survival Guide* (Microsoft Press, 1998).

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.

Integrated Defense Acquisition, Technology, and Logistics Life Cycle Management System



Speaker notes

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

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

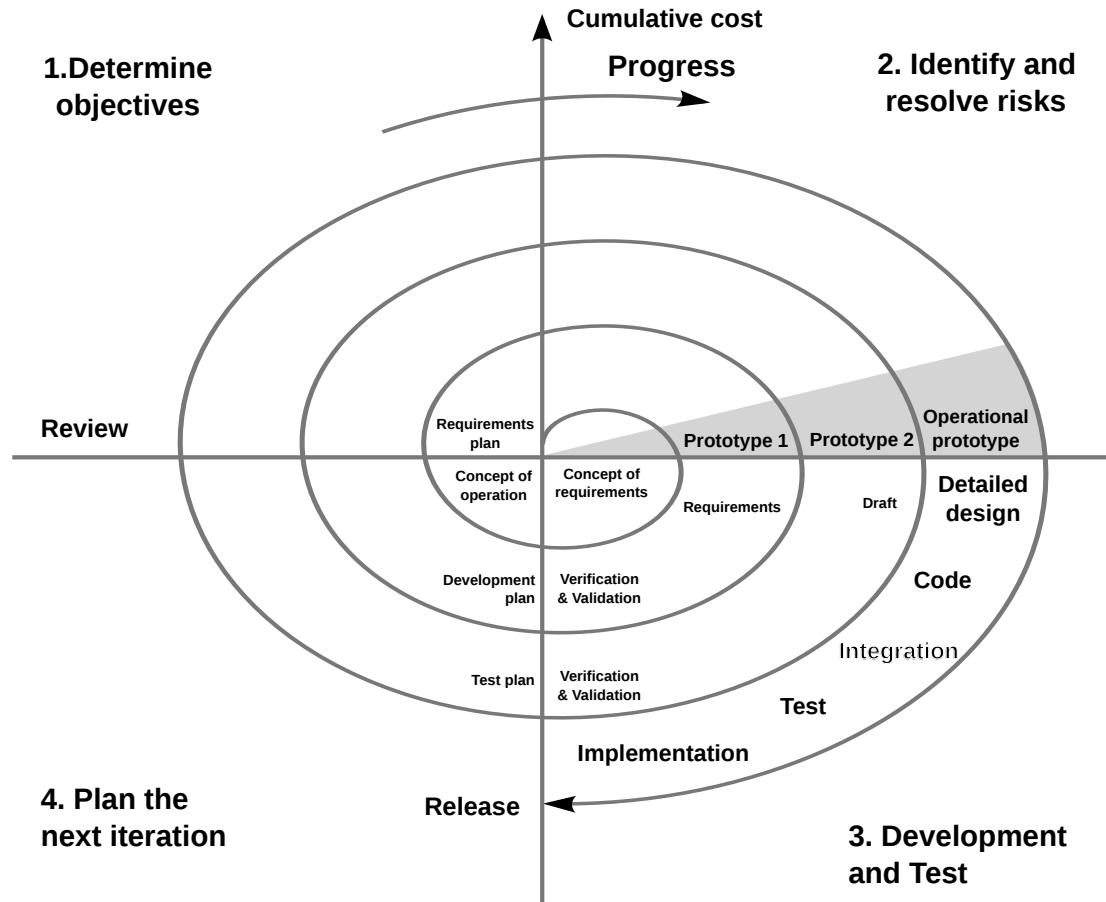


taming the chaos, understand requirements, plan before coding, remember testing

Speaker notes

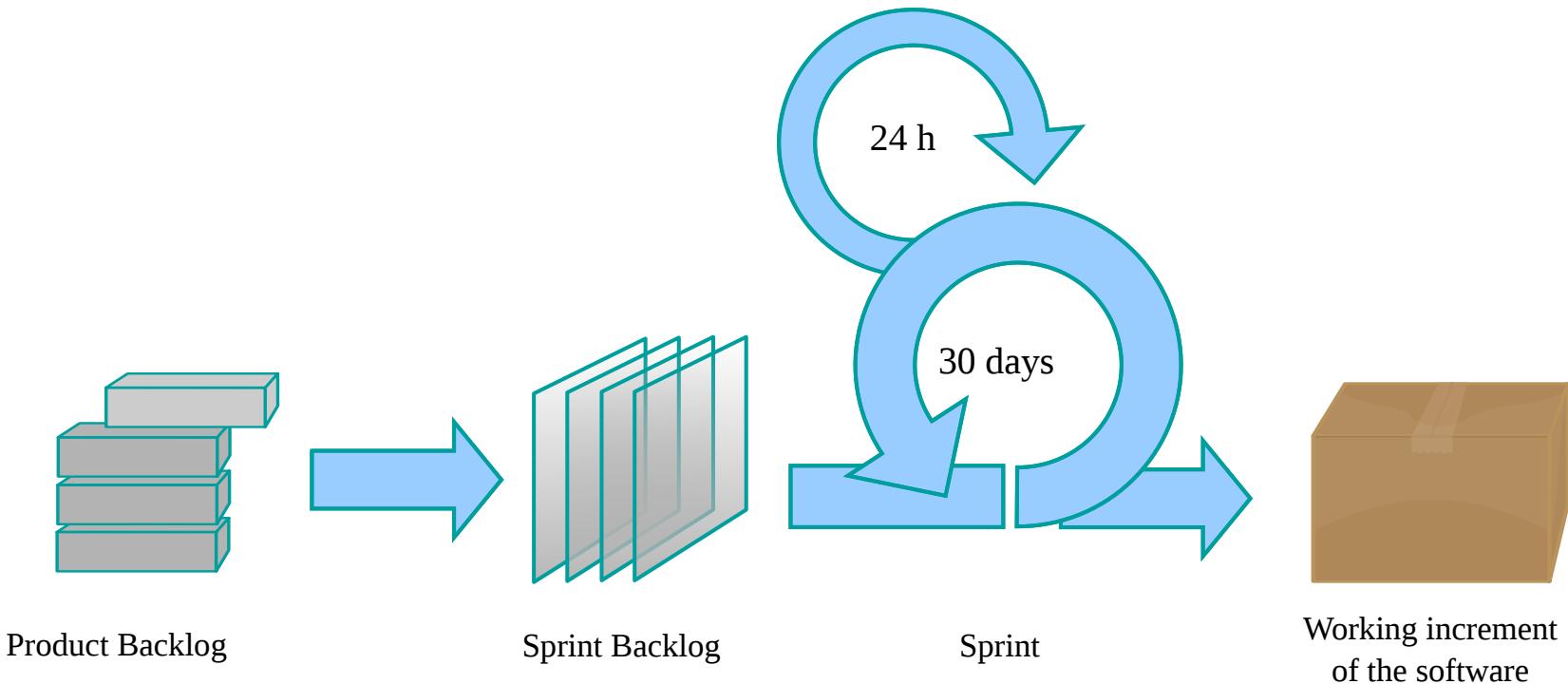
Although dated, the key idea is still essential -- think and plan before implementing. Not all requirements and design can be made upfront, but planning is usually helpful.

RISK FIRST: SPIRAL MODEL



incremental prototypes, starting with most risky components

CONSTANT ITERATION: AGILE



working with customers, constant replanning (CC BY-SA 4.0, Lakeworks)

SELECTING PROCESS MODELS

In slack, vote: [1] Ad-hoc [2] Waterfall [3] Spiral [4] Agile

And write a short justification in #lecture

The image shows the Zillow homepage. At the top, there is a navigation bar with links for 'Buy', 'Rent', 'Sell', 'Home Loans', 'Agent finder', 'Manage Rentals', 'Advertise', 'Help', and 'Sign in'. The main visual is a photograph of a two-story house with blue siding and yellow shutters. Overlaid on the image is the text 'Reimagine home' in large white letters and 'We'll help you find a place you'll love.' in smaller white letters. At the bottom, there is a search bar with the placeholder text 'Enter an address, neighborhood, city, or ZIP c...' and a magnifying glass icon.

DATA SCIENCE VS SOFTWARE ENGINEERING

DISCUSSION: ITERATION IN NOTEBOOK VS AGILE?

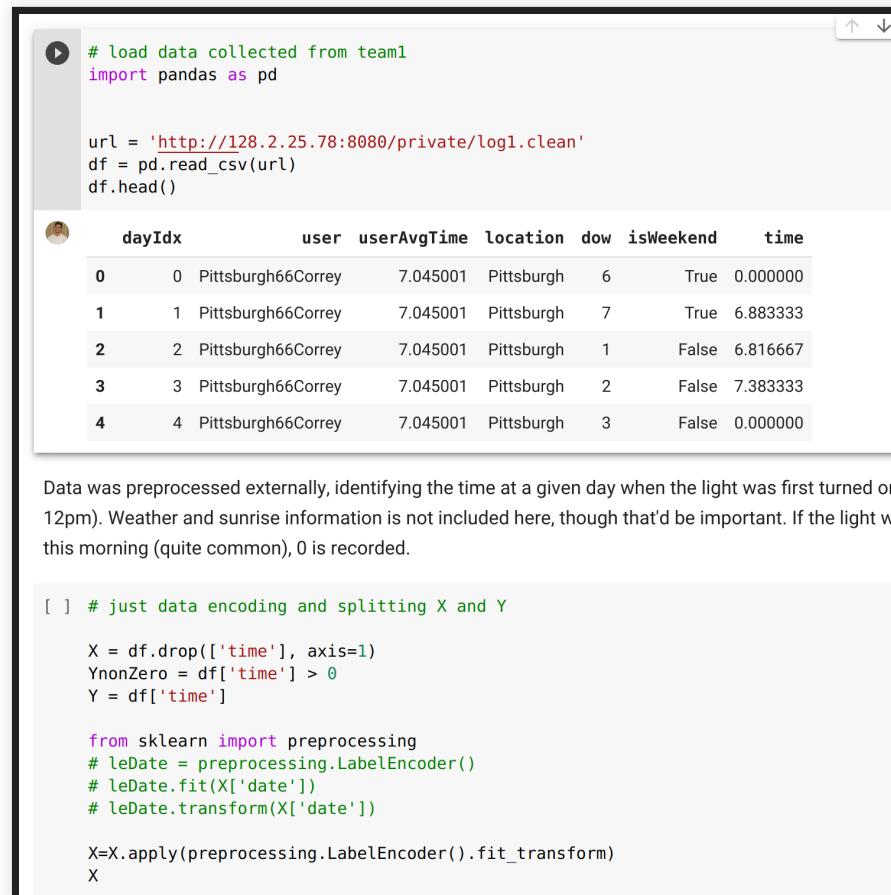


(CC BY-SA 4.0, Lakeworks)

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?



A screenshot of a Jupyter Notebook cell. The code cell contains:

```
# 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()
```

The output cell shows a DataFrame with 5 rows and 7 columns:

	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 was turned on this morning (quite common), 0 is recorded.

In the next cell, the code is:

```
[ ] # 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
```



- 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



A Venn diagram consisting of two overlapping circles. The left circle is light green and contains the text "Data Scientists". The right circle is light orange and contains the text "Software Engineers". The two circles overlap in the center.

Data
Scientists

Software
Engineers

DATA SCIENCE PRACTICES BY SOFTWARE ENGINEERS

- 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

INTEGRATED PROCESS FOR AI-ENABLED SYSTEMS

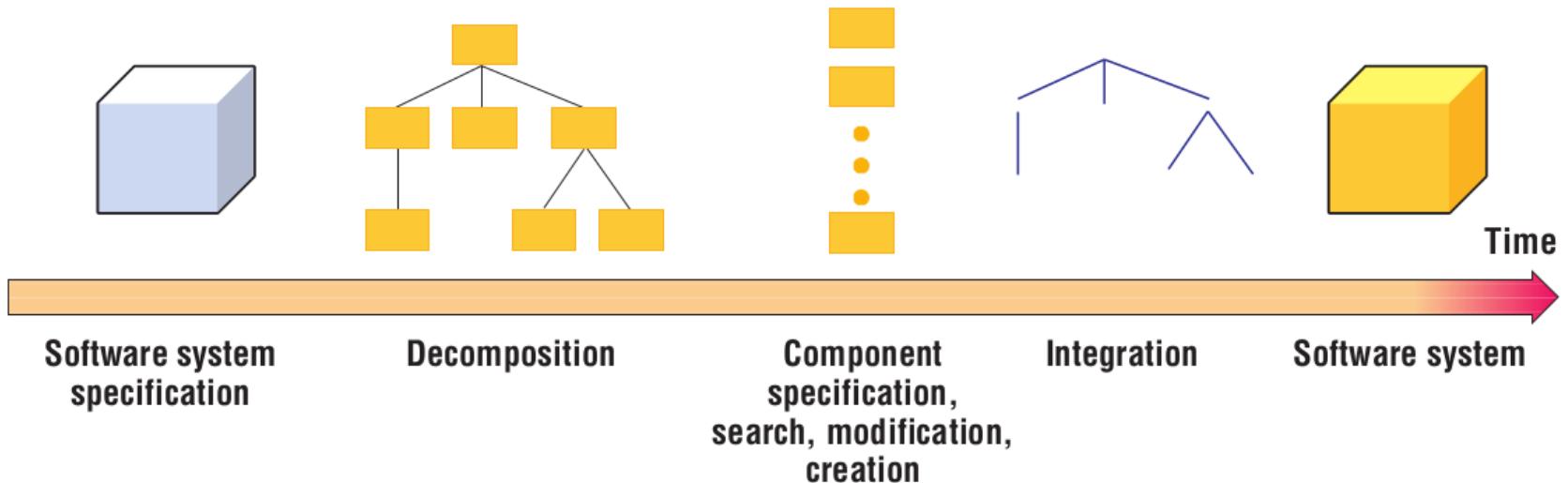


Figure from Dogru, Ali H., and Murat M. Tanik. “A process model for component-oriented software engineering.” IEEE Software 20, no. 2 (2003): 34–41.

Initial Requirements



Planning /
High-Level
Design



Low-Level
Design

Implemen-
tation



Quality
Assurance

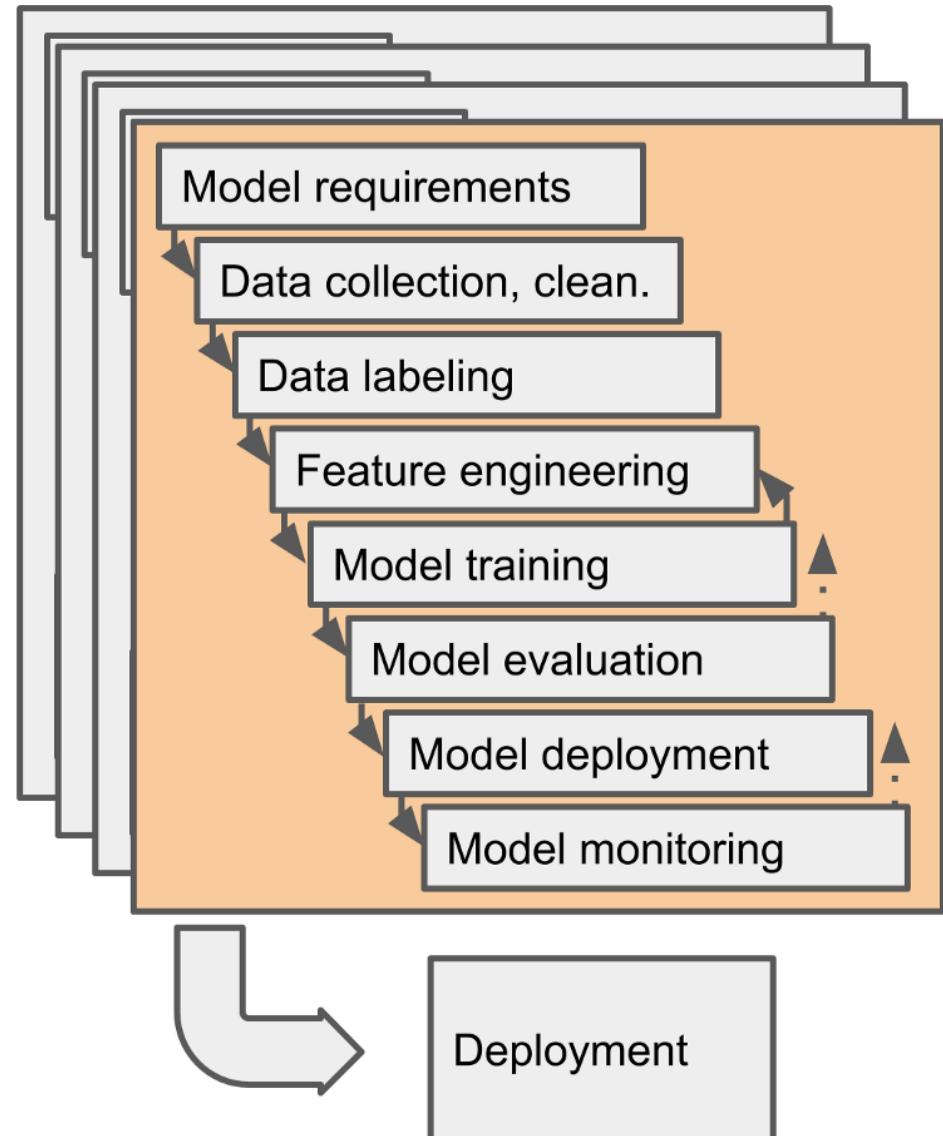
Deployment



Initial Requirements



Planning /
High-Level
Design



Deployment



System: Transcription service

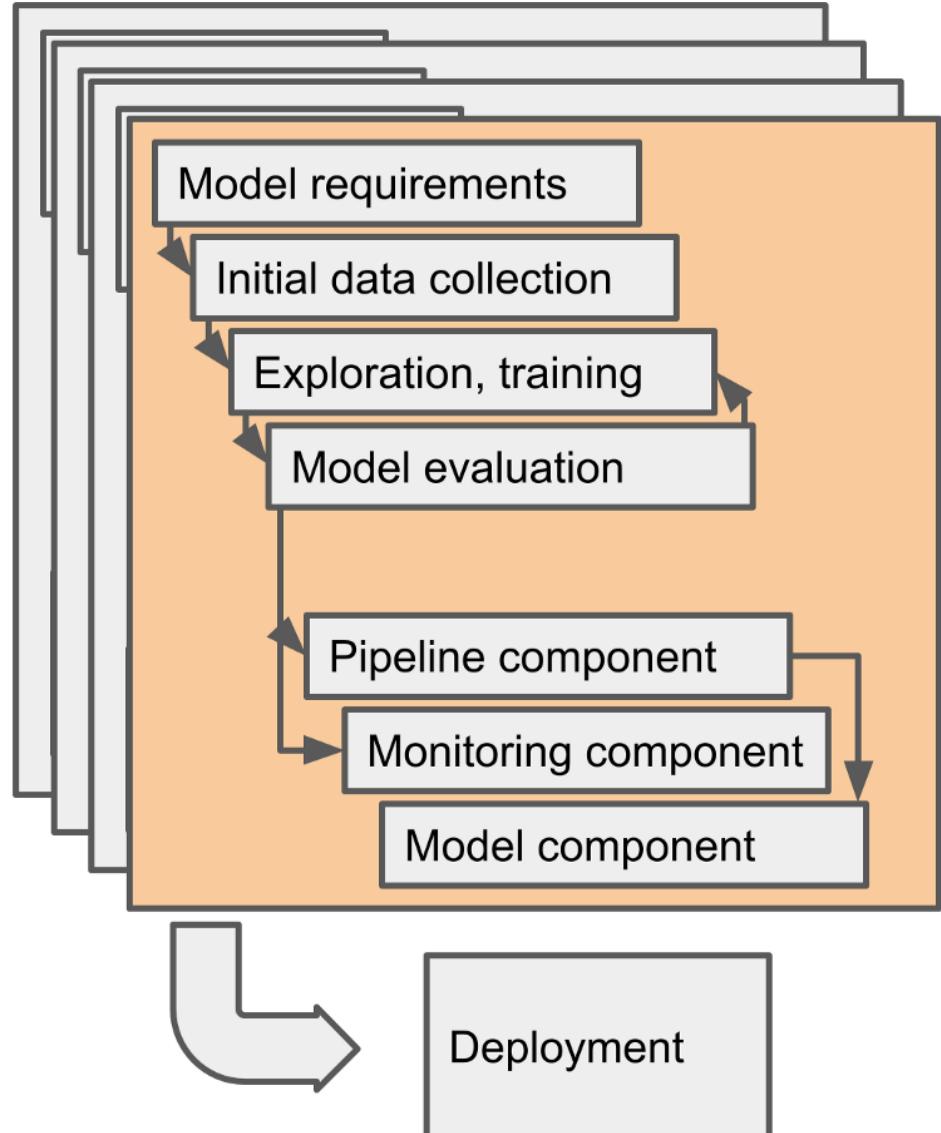


Legend: Non-ML component, ML component, system boundary

Initial Requirements



Planning /
High-Level
Design



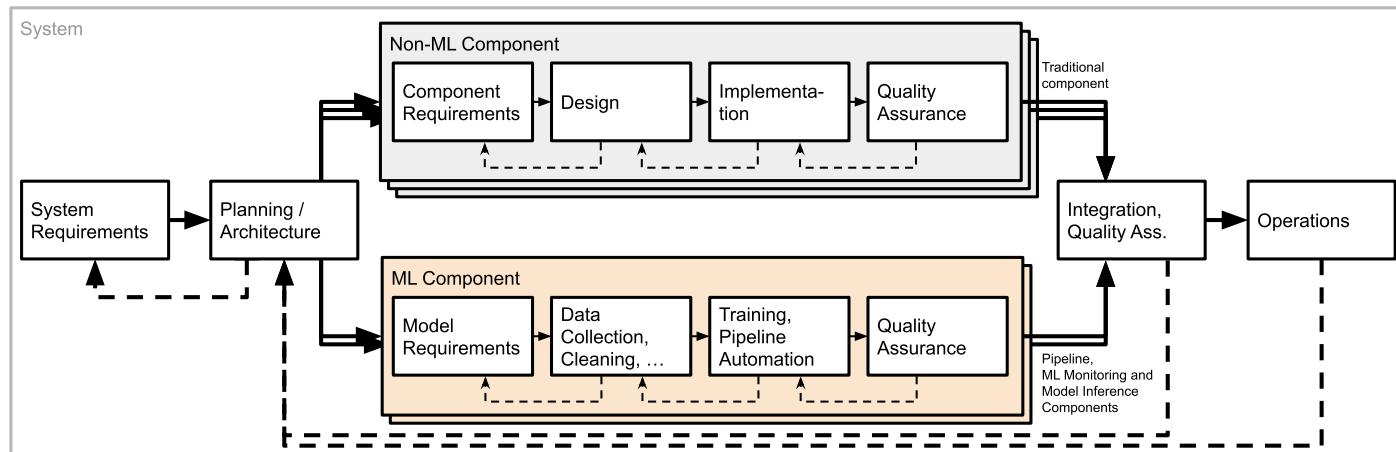


PROCESS FOR AI-ENABLED SYSTEMS

- 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



Buy Rent Sell Home Loans Agent finder



Manage Rentals Advertise Help Sign in



Reimagine home

We'll help you find a place you'll love.

Enter an address, neighborhood, city, or ZIP c...



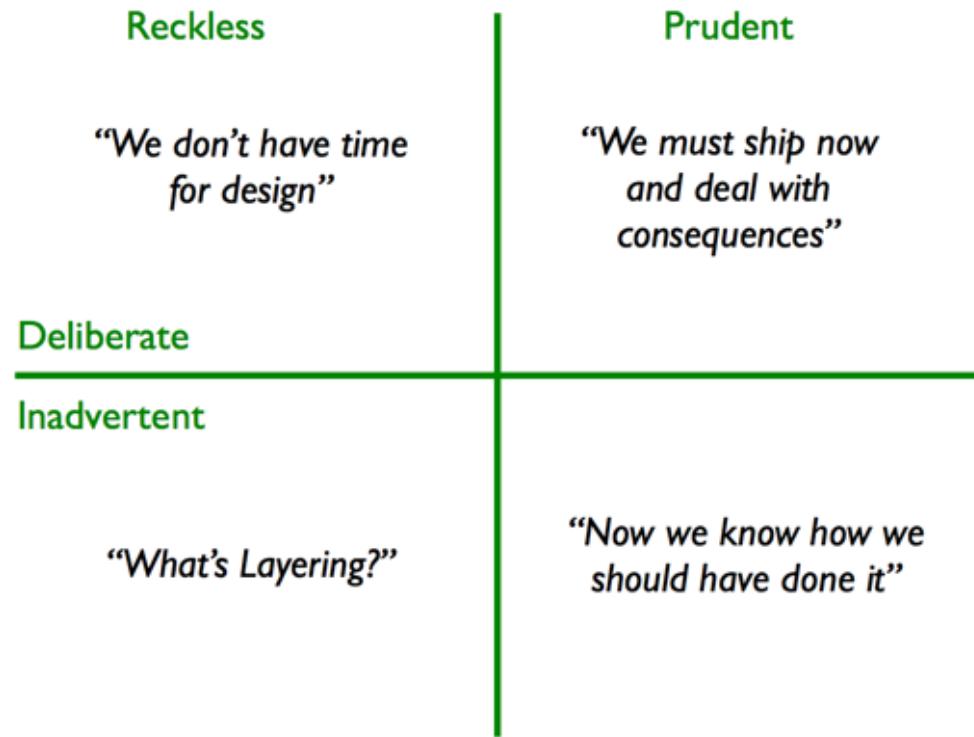
TECHNICAL DEBT



TECHNICAL DEBT METAPHOR

- Analogy to financial debt
 - Have a benefit now (e.g., progress quickly, release now)
 - accepting later cost (loss of productivity, e.g., higher maintenance/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

Examples?



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

TECHNICAL DEBT FROM ML COMPONENTS?

As a group in slack #lecture: Post two plausible examples technical debt in housing price prediction system:

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

Buy Rent Sell Home Loans Agent finder



Manage Rentals Advertise Help Sign in

A photograph of a two-story house with light-colored horizontal siding and dark shutters. The windows are illuminated from within, showing warm light. The sky is dark, suggesting it's nighttime.

Reimagine home

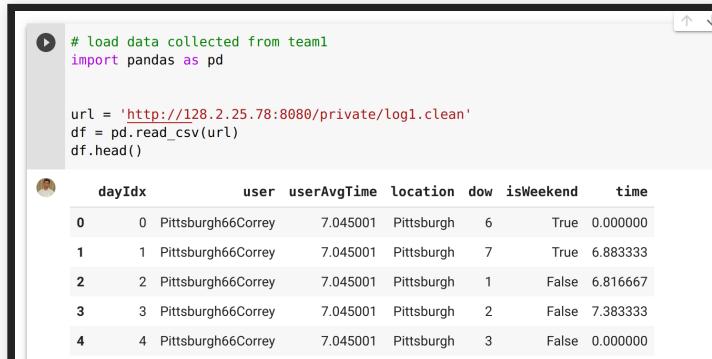
We'll help you find a place you'll love.

Enter an address, neighborhood, city, or ZIP c... 

Sculley, David, et al. [Hidden technical debt in machine learning systems](#). Advances in Neural Information Processing Systems. 2015.

THE NOTEBOOK

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



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 was off 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

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
 - 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



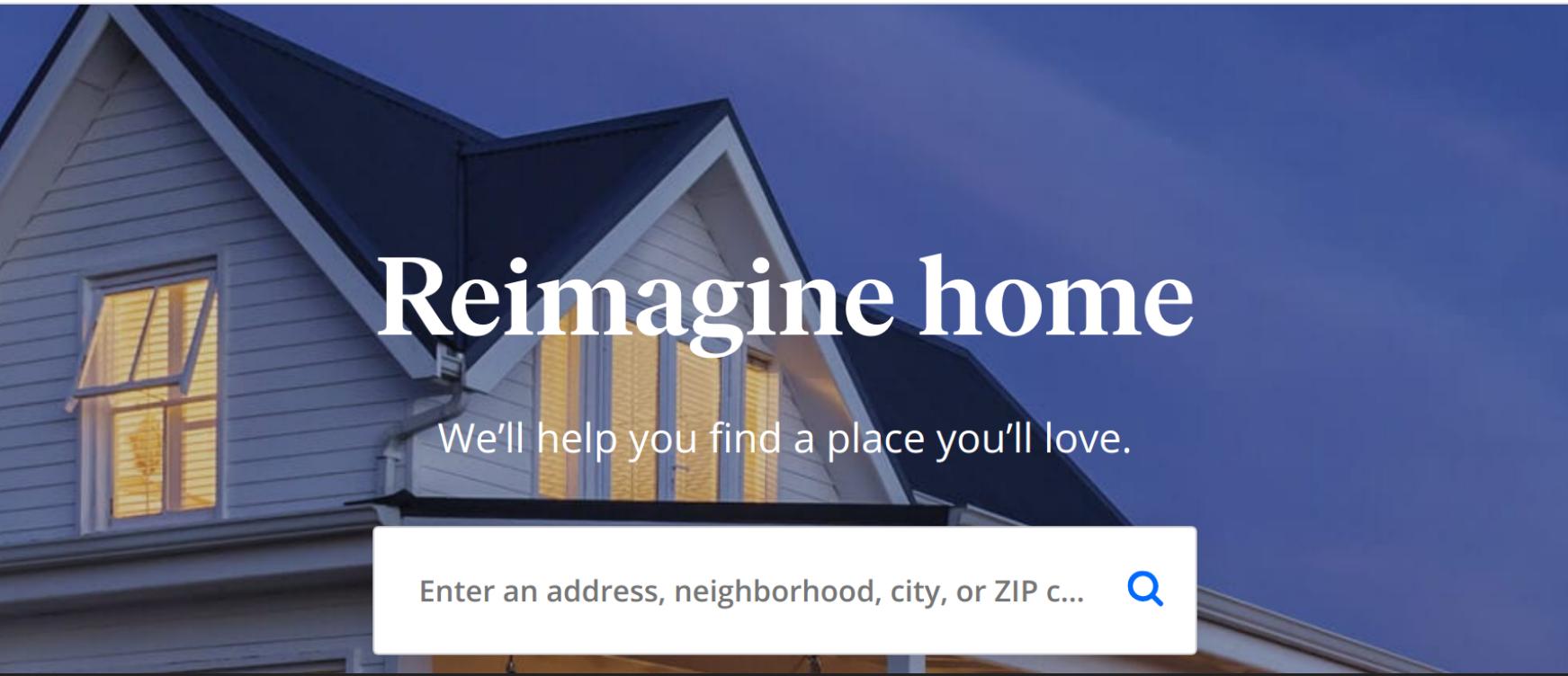
CONTROLLING TECHNICAL DEBT FROM ML COMPONENTS

- 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
- ...

Buy Rent Sell Home Loans Agent finder



Manage Rentals Advertise Help Sign in



Reimagine home

We'll help you find a place you'll love.

Enter an address, neighborhood, city, or ZIP c...



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) debt with machine learning

FURTHER READING

- On the process for building software with ML components
- Sculley, David, Gary Holt, Daniel Golovin, Eugene Davydov, Todd Phillips, Dietmar Ebner, Vinay Chaudhary, Michael Young, Jean-Francois Crespo, and Dan Dennison. "[Hidden technical debt in machine learning systems.](#)" In Advances in neural information processing systems, pp. 2503-2511. 2015.
- Studer, Stefan, Thanh Binh Bui, Christian Drescher, Alexander Hanuschkin, Ludwig Winkler, Steven Peters, and Klaus-Robert Mueller. "[Towards CRISP-ML \(Q\): A Machine Learning Process Model with Quality Assurance Methodology.](#)" arXiv preprint arXiv:2003.05155 (2020).
- Martínez-Plumed, Fernando, Lidia Contreras-Ochando, Cesar Ferri, José Hernández Orallo, Meelis Kull, Nicolas Lachiche, Maréa José Ramírez Quintana, and Peter A. Flach. "[CRISP-DM Twenty Years Later: From Data Mining Processes to Data Science Trajectories.](#)" IEEE Transactions on Knowledge and Data Engineering (2019).

FURTHER READING 2

- Patel, Kayur, James Fogarty, James A. Landay, and Beverly Harrison. "[Investigating statistical machine learning as a tool for software development](#)." In Proceedings of the SIGCHI Conference on Human Factors in Computing Systems, pp. 667-676. 2008.
- 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.