

Datas Importantes

Atos acadêmicos no SIGA - Calendário Trimestral	1º Trimestre	2º Trimestre	3º Trimestre	4º Trimestre
Início de atividades	06/07/2020	13/10/2020	01/02/2021	----- X -----
Rematricula de matrícula trancada (destrancamento de matrícula)	Até 27/06/2020	Até 05/10/2020	Até 23/01/2021	----- X -----
Previsão de turmas	Até 19/06/2020	Até 26/09/2020	Até 15/01/2021	----- X -----
Trancamento de matrícula	Até 10/08/2020	Até 17/11/2020	Até 08/03/2021	----- X -----
Pedido de inscrição em disciplinas	De 06/07/2020 a 24/07/2020	De 11/10/2020 a 17/10/2020	De 30/01/2021 a 05/02/2021	----- X -----
Concordância do pedido de inscrição em disciplina	De 27/07/2020 a 30/07/2020	De 18/10/2020 a 24/10/2020	De 06/02/2021 a 12/02/2021	----- X -----
Efetivação do Pedido de Inscrição (Divisão de Ensino – PR2)	31/07/2020	27/10/2020	15/02/2021	----- X -----
Pedido de alteração de inscrição em disciplina – AID	De 02/08/2020 a 08/08/2020	De 28/10/2020 a 31/10/2020	De 16/02/2021 a 19/02/2021	----- X -----
Concordância do pedido de alteração de inscrição em disciplina - AID	De 09/08/2020 a 12/08/2020	De 01/11/2020 a 07/11/2020	De 20/02/2021 a 26/02/2021	----- X -----
Efetivação De Alteração do Pedido de Inscrição (Divisão de Ensino – PR2)	13/08/2020	10/11/2020	01/03/2021	----- X -----
Pedido de trancamento de inscrição em disciplina (desistência de inscrição)	De 14/08/2020 a 19/08/2020	De 11/11/2020 a 14/11/2020	De 02/03/2021 a 05/03/2021	----- X -----
Concordância do pedido de trancamento de inscrição em disciplina	De 20/08/2020 a 31/08/2020	De 15/11/2020 a 28/11/2020	De 06/03/2021 a 19/03/2021	----- X -----
Efetivação do Trancamento do Pedido de Inscrição (Divisão de Ensino – PR2)	24/08/2020	01/12/2020	22/03/2021	----- X -----
Término de atividades	03/10/2020	16/01/2021	24/04/2021	----- X -----
Notas – Pautas de graus e frequência	De 04/10/2020 a 17/10/2020	De 17/01/2021 a 30/01/2021	De 25/04/2021 a 08/05/2021	----- X -----

Avaliação e Atendimento

Critérios de aprovação são os do PPGI/UFRJ.

A avaliação da disciplina consiste em participação em sala de aula (P); exercícios e/ou protótipos desenvolvidos (E); apresentações/ /escritas de artigos (A).

$$MF = 0.2 * P + 0.2 * E + 0.6 * A$$

O aluno que desejar atendimento deverá requisitar o mesmo por e-mail e um horário será agendado pelos responsáveis para o atendimento.



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Entregáveis – Março

4/3 - Aula + Definição dos grupos + PIT 5 min (Apresentação geral em PPT - DataSet + Problema + Objetivo)

11/3 - Aula + Descrição do projeto de DS - Tudo é via GIT!

- Entregar o projeto contendo (V1): Detalhamento e descrição textual da definição do problema a ser explorado pela equipe; descrever tecnicamente o dataset e sua fonte, o que pretendem fazer e o que vão e como extrair (plano dos experimentos). Apresentar os objetivos geral e específico do projeto de DS; apresentar métodos de data cleaning/tratamento de dados que serão usados, apresentar a proposta de modelo de extração de conhecimento e visualização de dados que será adotado.

18/3 - Aula + Refinamento do projeto de DS

- Agregar ao projeto (V2) : Plano do experimento a ser executado (scripts no Colab x Jupyter x IDE), projeto de coleta de metadados da proveniência dos experimentos, projeto para tornar seu experimento reproduzível, adicionar qualquer outro melhoria ou diferencial que julguem necessário

25/3 – Aula + entregar da 1a versão do artigo – Recomenda-se usar o template da LNCS e suas regras de formatação.

- Texto final (15-20) páginas com referências (pode ser em português ou inglês, escolha do grupo)

Entregáveis - Abril

1/4 - Aula

8/4 - Aula + Sorteio ordem de apresentação dos grupos

15/4 - Entregar da 2ª versão do artigo + Apresentação trabalho alunos (1ª. Parte dos grupos)

22/4 - Apresentação - trabalho alunos (2ª. Parte dos grupos)

10/5 (?) - Entrega da versão final do artigo + projeto completo (V3) + scripts com provenance + datasets anotados + resultados de DS + Depósito do notebook reprodutível e executáveis no GIT



Introduction to Data Science

MODULE IV – PART II

Scientific in Silico Experiments as
Workflows and Scripts

Prof Sergio Serra e Jorge Zavaleta

What? The Modeling Process

Ask an interesting question
& learn reproducibility

Get the Data

Explore the Data

Model the Data

Communicate/Visualize the Results

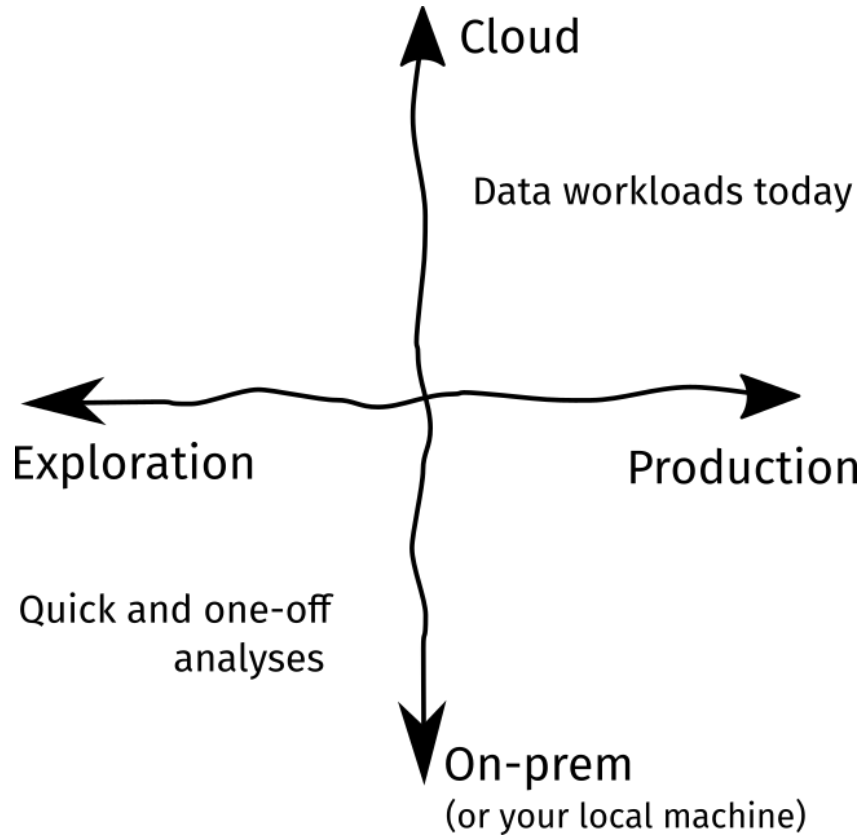
How were the model made?

Which model is relevant?

Who made it and when/how its executed?

Module III and IV

The data science landscape today



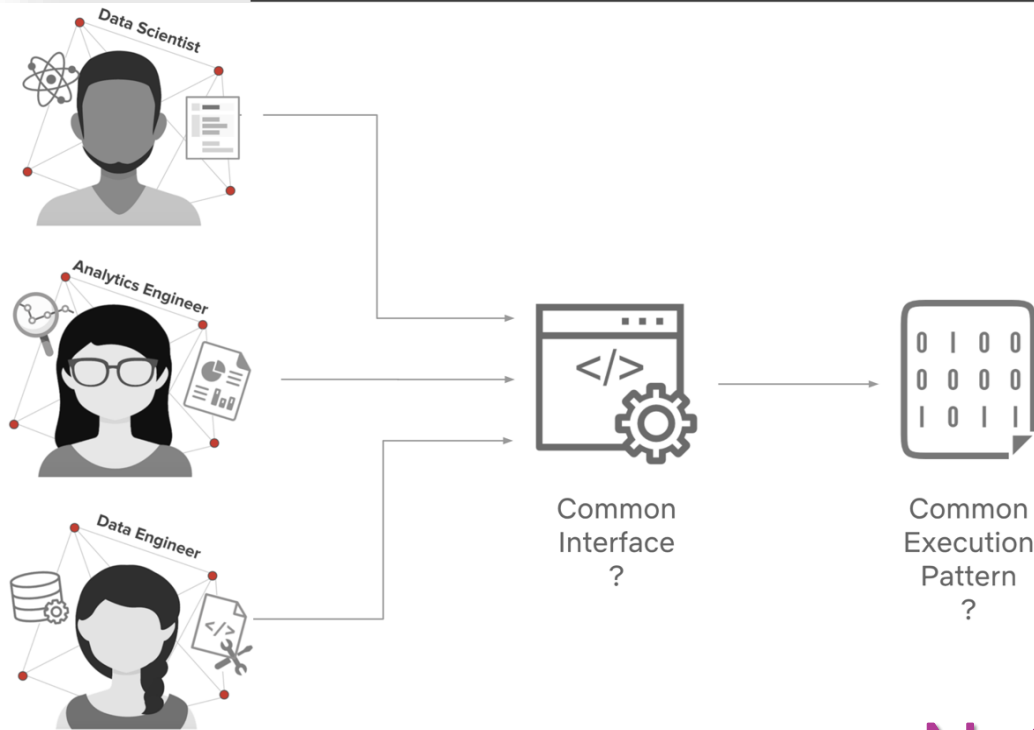
Data science is rapidly changing...

Phrases like “sexiest job of the 21st century” and “data is the new oil” have become old and replaced by more realistic **business problems and grounded technical challenges.**

The changes are three-fold: **We need to support both the**

- (1) Demand for productionizing analyses and experiments,
- (2) Rapid adoption of the Cloud,
- (3) Different data user needs

Our (future) data users



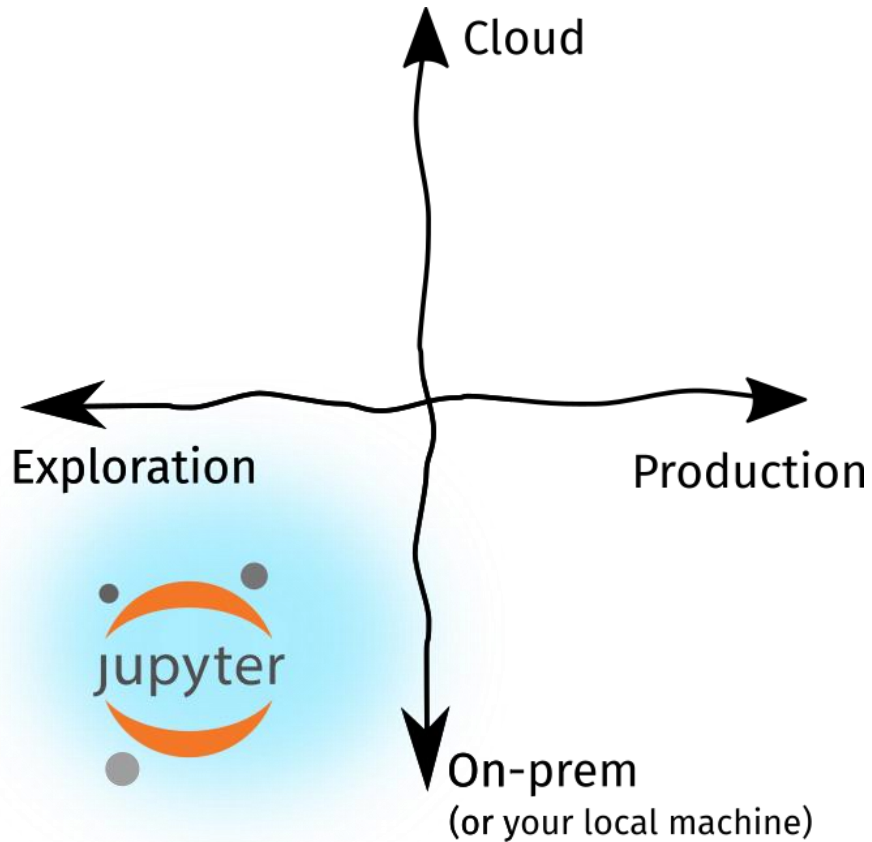
Data science teams grow (confluence of users). Unfortunately, their toolsets and workstyles vary a lot. To look forward at (future) needs, we ask a few basic questions:

- What interface will a **data analyst** use to chart a few combined queries into a business report?
- How will a **data engineer** write code that a reliability engineer can help ensure runs every hour?
- How will a **machine learning developer** encapsulate a model iteration their colleagues can reuse?

Notebooks.

- Shareable
- Easy to Read
- Documentation with
- Code
- Outputs as Reports
- Familiar Interface
- Multi-Language

Notebooks: Woes To Wins...



The Good

- Quick iteration cycles
- Recorded outputs
- Easy to modify

The Bad

- Lack of history (version and provenance)
- Easy to modify

The Ugly

- Concurrent edits
- Browser state

...production gaps to fill

Things to preserve:

- Results linked to code
- Good visuals
- Easy to share

Things to improve:

- Not versioned
- Mutable state
- Templating
- Provenance

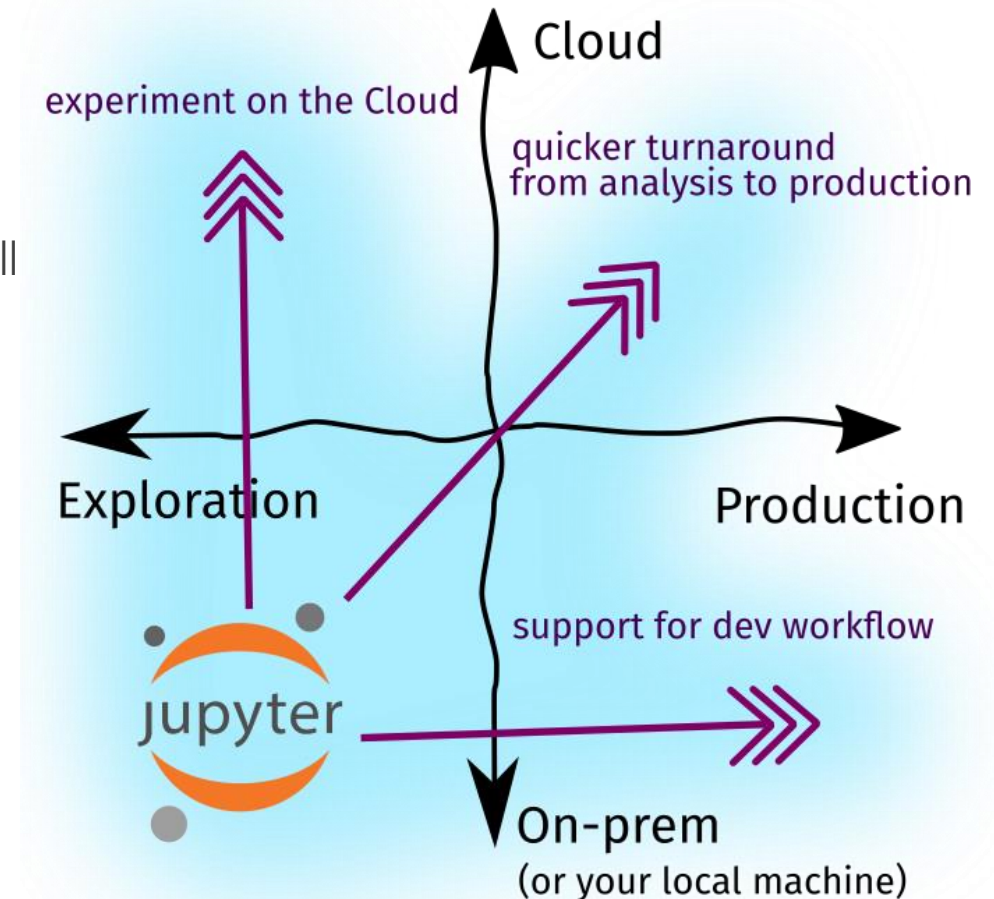
The three forces of change

Jupyter Notebook ecosystem is growing, three forces:

1- **Experiment on the Cloud:** big data demands large compute and storage, something that your average consumer-grade machine will not always be capable of.

2- **Support for developer workflow:** more and more data science teams are starting to adopt software engineering best practices—version-control, gitflow, pull requests, and more.

3- **Quick turnaround from analysis to production/research:** it's not enough to test hypotheses under controlled environments. Software written for analysis should be easily reused for prod.



The growth of the Notebook ecosystem is driven by these forces

The three forces of change

- Growing towards a more **Cloud-first environment** means → perform Notebook-based tasks in machines more powerful than our own.
 - For example, managed notebook instances enabled us to run Jupyter notebooks from a remote server with no-ops and setup.
- Growing towards a more **production workflow** provides us with a set of tools to endow our notebook-based tasks with **software engineering practices**.
 - the growth of a tool doesn't depend on a single entity or organization. Filling these gaps may stem from individuals who contribute **third-party plugins** or organizations offering **managed services from notebooks**.

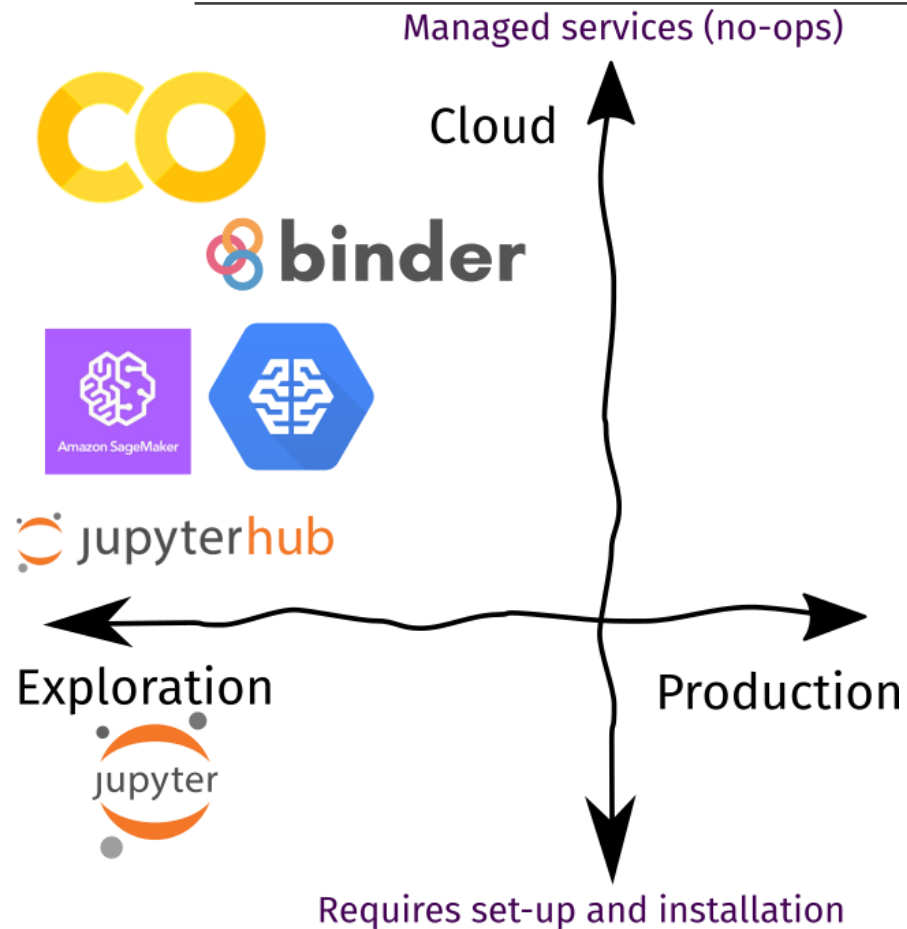
A photograph of the Golden Gate Bridge in San Francisco, viewed from a low angle looking down the length of the bridge towards the far tower. The bridge's iconic orange-red color is visible on the tower and cables. The water below is a deep blue, and the sky is a pale blue with some light clouds. The bridge's structure, including the suspension cables and the deck, is clearly visible.

How to improve the growing force using Jupyter Notebooks in 2021?

The three forces in focus

1. Experiment on the Cloud
2. Support for developer workflow
3. Quick turnaround from prototype to production or research

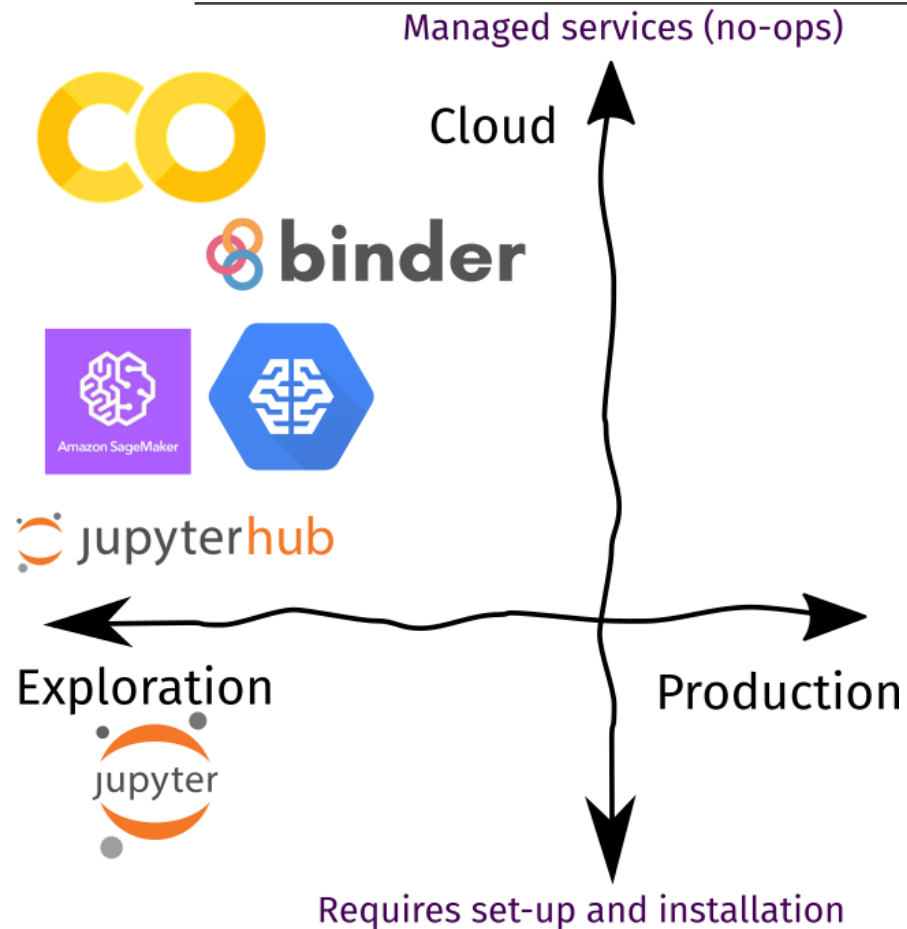
1- Experiment on the Cloud



A huge component of the **data science workflow** is **experimentation**. It includes engineering, hyperparameter optimization, and testing-out models.

As data gets bigger and models get more compute-intensive, it is not enough to do everything on your laptop. Experimentation workloads are often delegated to the Cloud.

1- Experiment on the Cloud



	Recommendation
Best Tool of Choice	Google Colaboratory . With Colab, you have immediate access to powerful hardware for your experiments.
Runner-up	If you are on a Cloud Platform. Check-out managed notebook instances in AWS Sagemaker or Google Cloud's AI Platform .
Check out	Binder for “publishing” finished work, and JupyterHub if you wish to setup your own managed notebook instances.

2- Support for developer workflow

As data science teams grow, we see a confluence of researchers and engineers working together. Unfortunately, their toolsets and workstyles vary a lot.

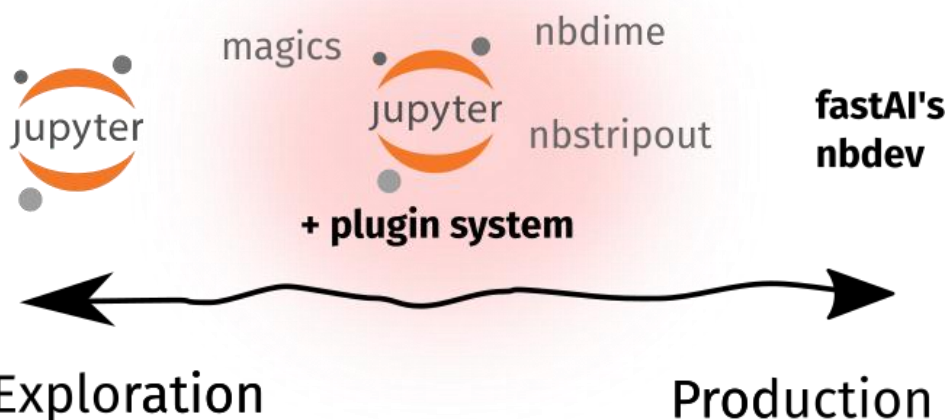
- Engineers are comfortable with text editors and IDEs, while some researchers find Jupyter Notebooks convenient. Sometimes engineers disdain notebooks, researchers who aren't familiar with concepts like DRY or KISS 😊😊😊

In an ideal world, everyone uses the same thing and we're all happy. However, in practice.....

- (1) Engineers supporting the tools comfortable for researchers, and
- (2) Researchers learning basic software engineering principles.

2- Support for developer workflow

Focus on software eng'g principles



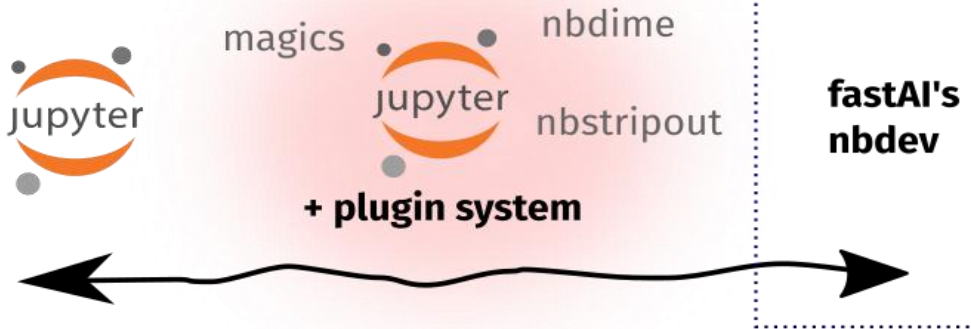
	In Jupyter-ecosystem	External
Best Tool of Choice	nbdime and nbstripout emulate the Git developer workflow	cookiecutter-datascience to set up a more organized project structure
Runner-up	nbconvert commit your files into a more human-friendly text format	data-version control (DVC) so that you won't "pollute" your Git repo with model files (can reach GBs) or non-essential doc types (Excel sheets, PDFs, etc.)
Check-out	fast.AI's nbdev as a highly-opinionated way of developing everything in the context of notebooks.	

2- Support for developer workflow

Focus on software eng'g principles



Full-fledged
"notebook IDEs"



Exploration

Production

it encourages two things: modularization and documentation.

Modularization means that if you have copy-pasted functions scattered across multiple notebooks, then don't repeat yourself, and put them in a module where you can define them once and import anywhere.

Documentation, is the practice of writing text to accompany your analyses and code.

- My suggestion is to document aggressively: learn about Python docstrings, Sphinx, or simple Markdown.

Jupyter Notebooks aren't suited for a Git-like workflow. Even if they're just a JSON text file, they become quite unruly when checking for diffs or *gulps* resolving conflicts.

- Try a combination of **nbstripout** and **nbdime**.

3- Quick turnaround from prototype to production or research

This means that an engineer/researcher can treat Notebooks as **blackboxes** with expected inputs and outputs, then run it as she would any other process.

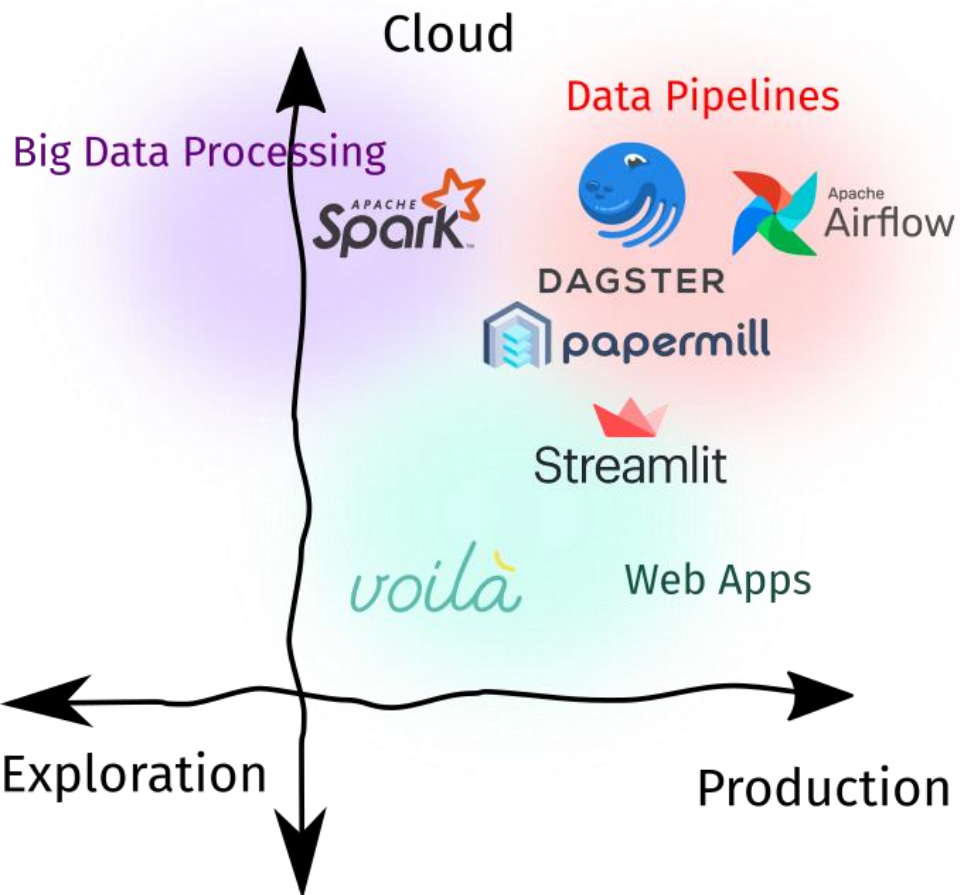
- How notebooks behave as software components? and how it integrates with some standard engineering tools?

Using notebooks in production or research is a highly-debated topic. There may be merits in using Notebooks, but it is important for data science teams to evaluate if a Notebook or the standard stack is the right tool for the job.

There are lots of tools that support bringing Notebooks into production/reproducible research.

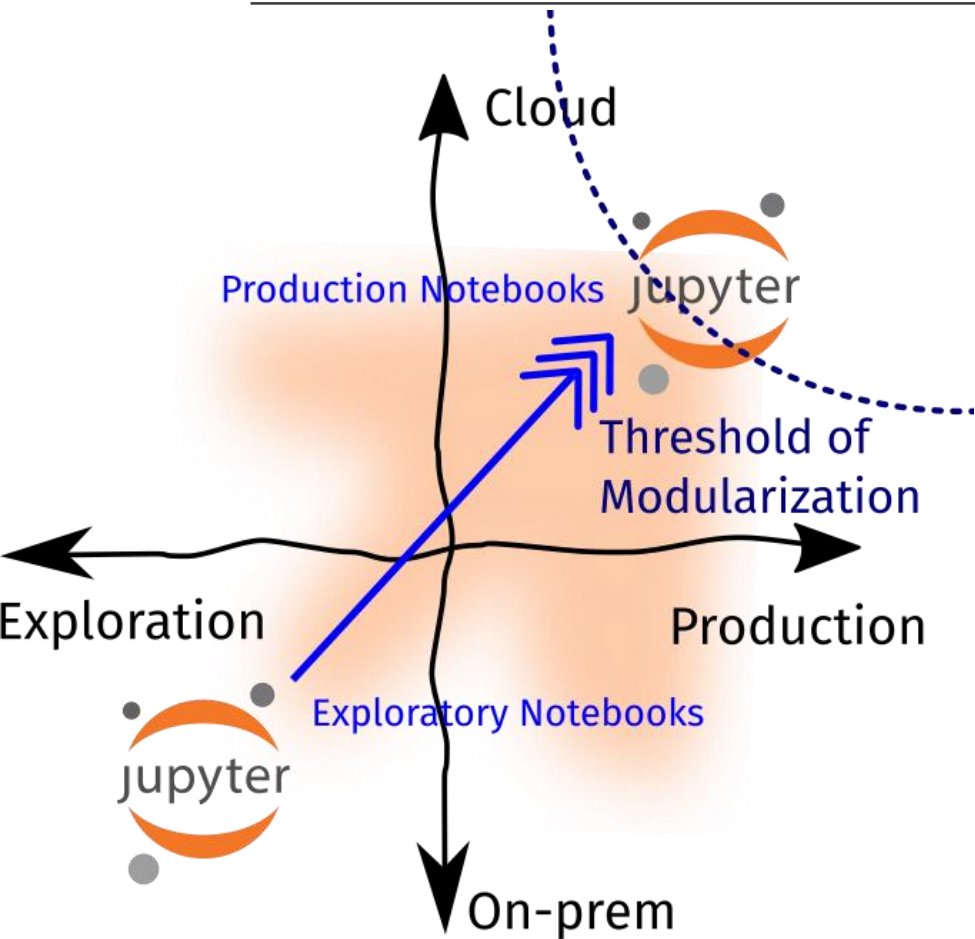
- **Components of a data pipeline:** Notebooks can be thought of as a function that takes in an input, transforms it, and returns an output.
 - For example, it can be used to obtain embeddings from an image before storing it into a distributed filesystem, a final layer in a data pipeline to generate templated reports, or a batch ML service that outputs some predictions for downstream tasks.
- **Web-application:** Interactivity is one of the main features of Jupyter Notebooks.
 - On one end you can intersperse code with text, then on the other, you can put widgets for control. Nowadays, there are tools that convert Notebooks into a fully-fledged web application or reproducible research
- **Big data processing interface:** We used to analyze Big Data using SQL, Hive, or some other DSL.
 - We can replace this interface with a Notebook-like point-of-contact. This gives enough expressiveness (since we're using Python) to quickly analyze petabyte-scale datasets.

3- Quick turnaround from prototype to production or research



	Recommendation
Best Tool of Choice	Papermill for parametrizing and running notebooks as you'd do for Python scripts. Streamlit , although not Jupyter-native, can be used to create web-apps in-tandem with nbconvert.
Runner-up	Voila for a Jupyter-native experience of building web-apps, and Apache Spark for Big Data Analysis.
Check out	Dagster (Dagstermill) and Airflow (PapermillOperator) for Notebook-based data pipelines. Although I recommend that for critical ETLs, traditional Python scripts should be considered.

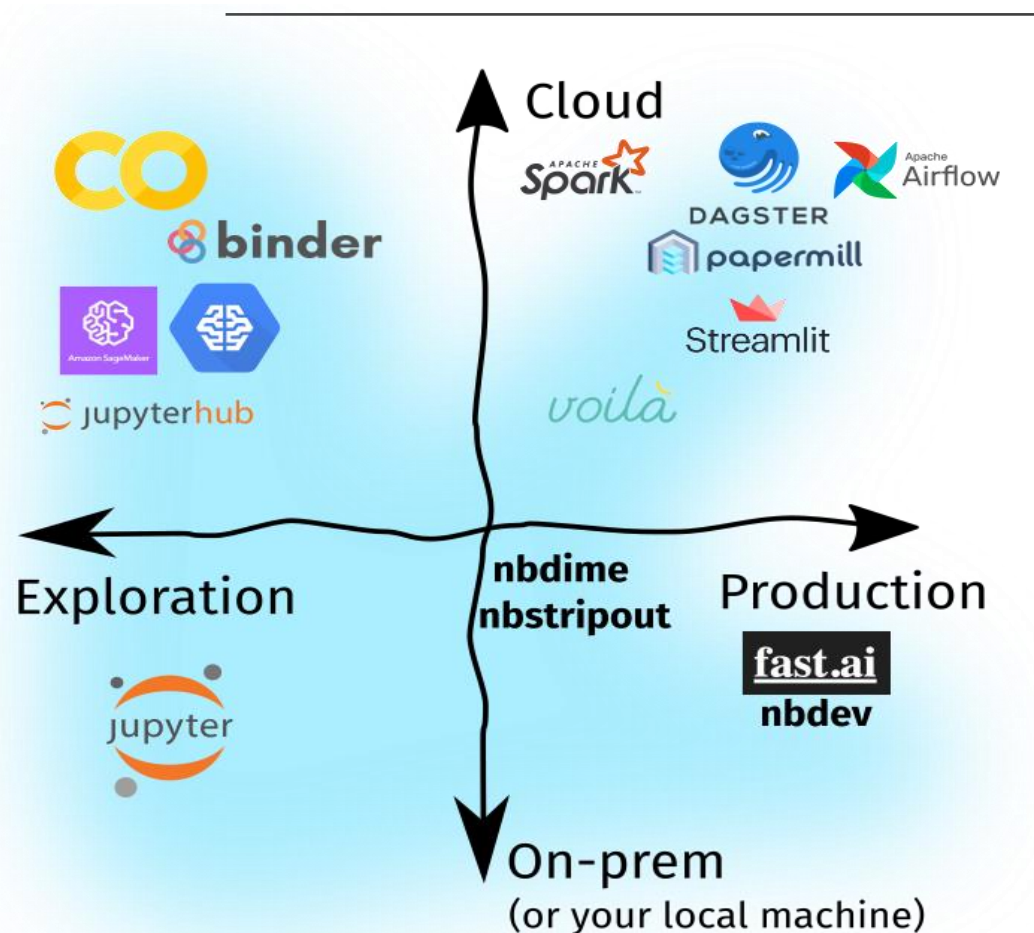
Putting-it together



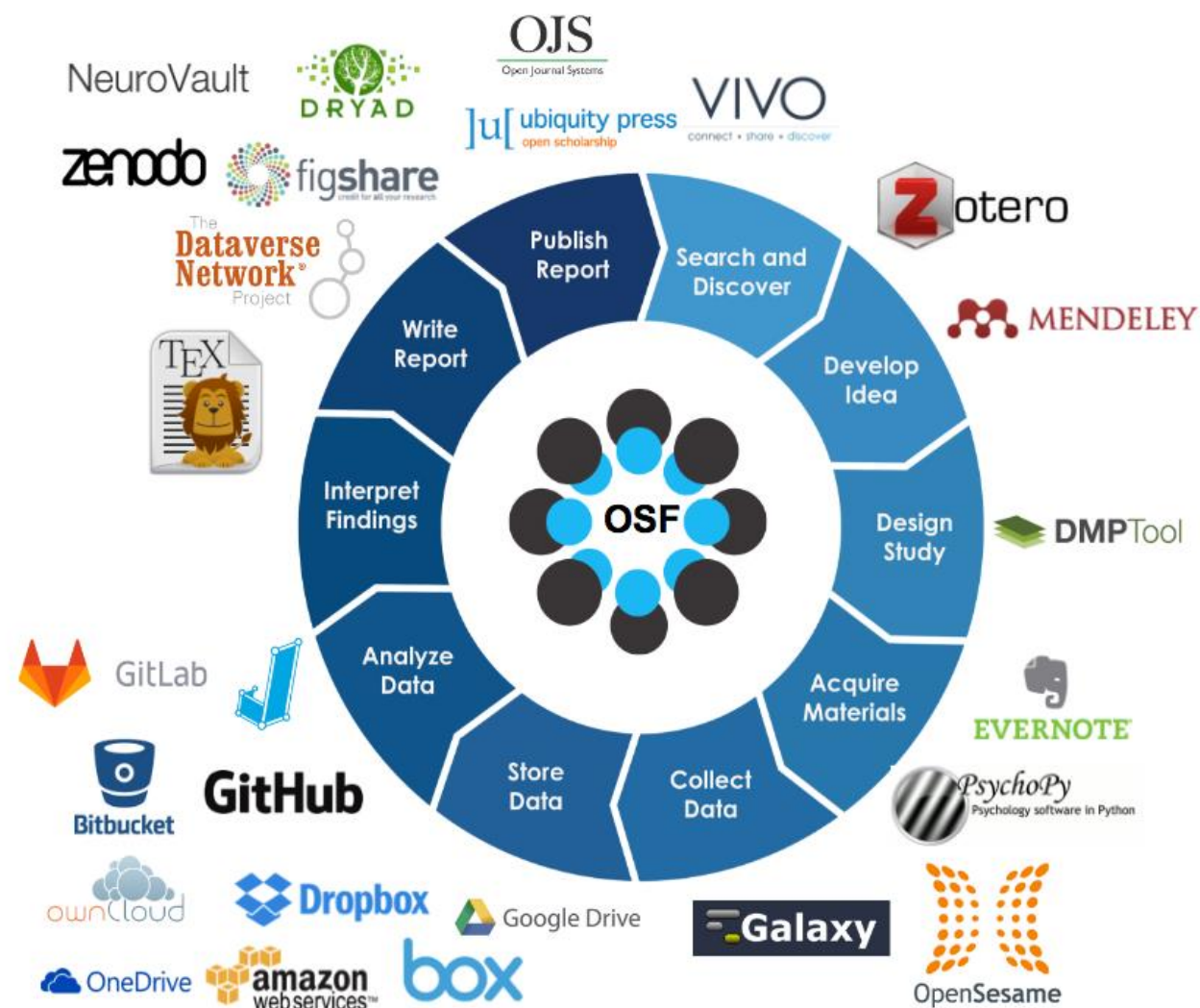
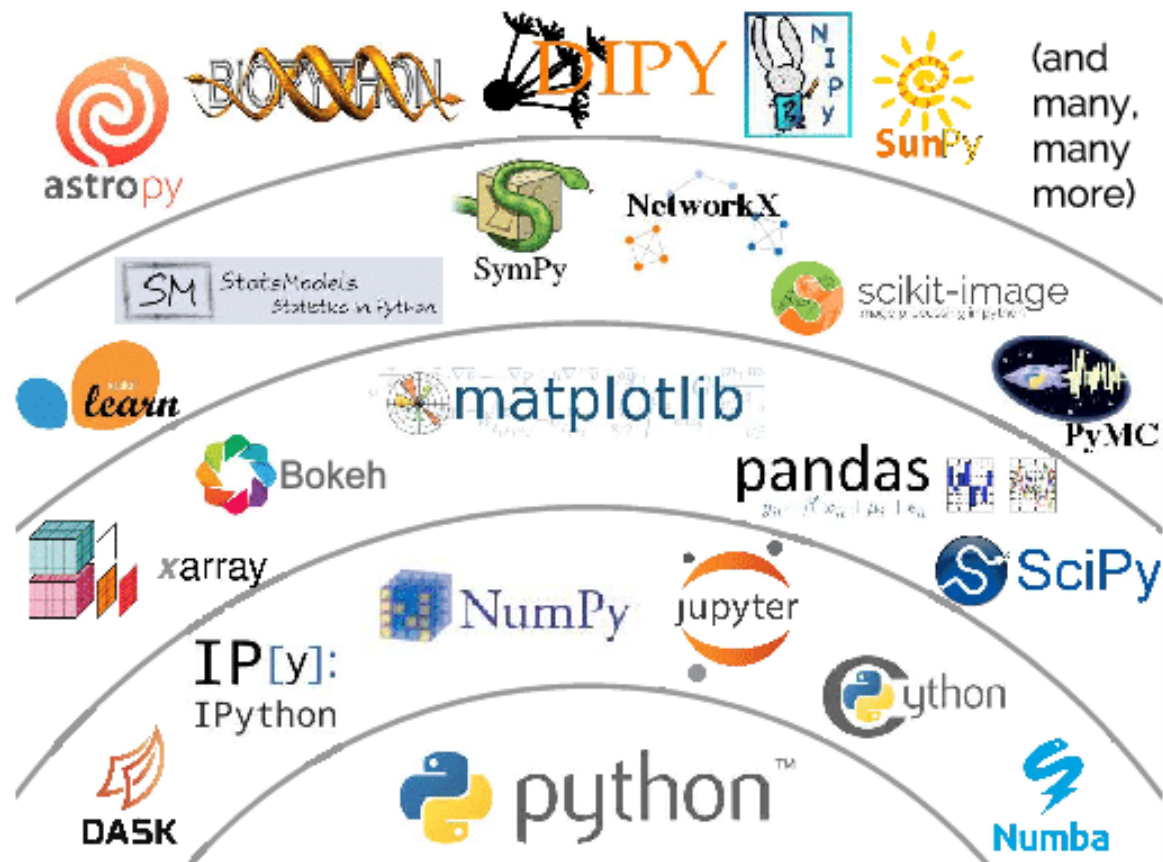
This means... even if you start with some **ad-hoc and dirty analyses**, You **always need to update** them so that you (or other people) can **rerun** them seamlessly and understand my methods in the future...

How to e convert exploratory Notebooks to Production/Reproducible research ones?

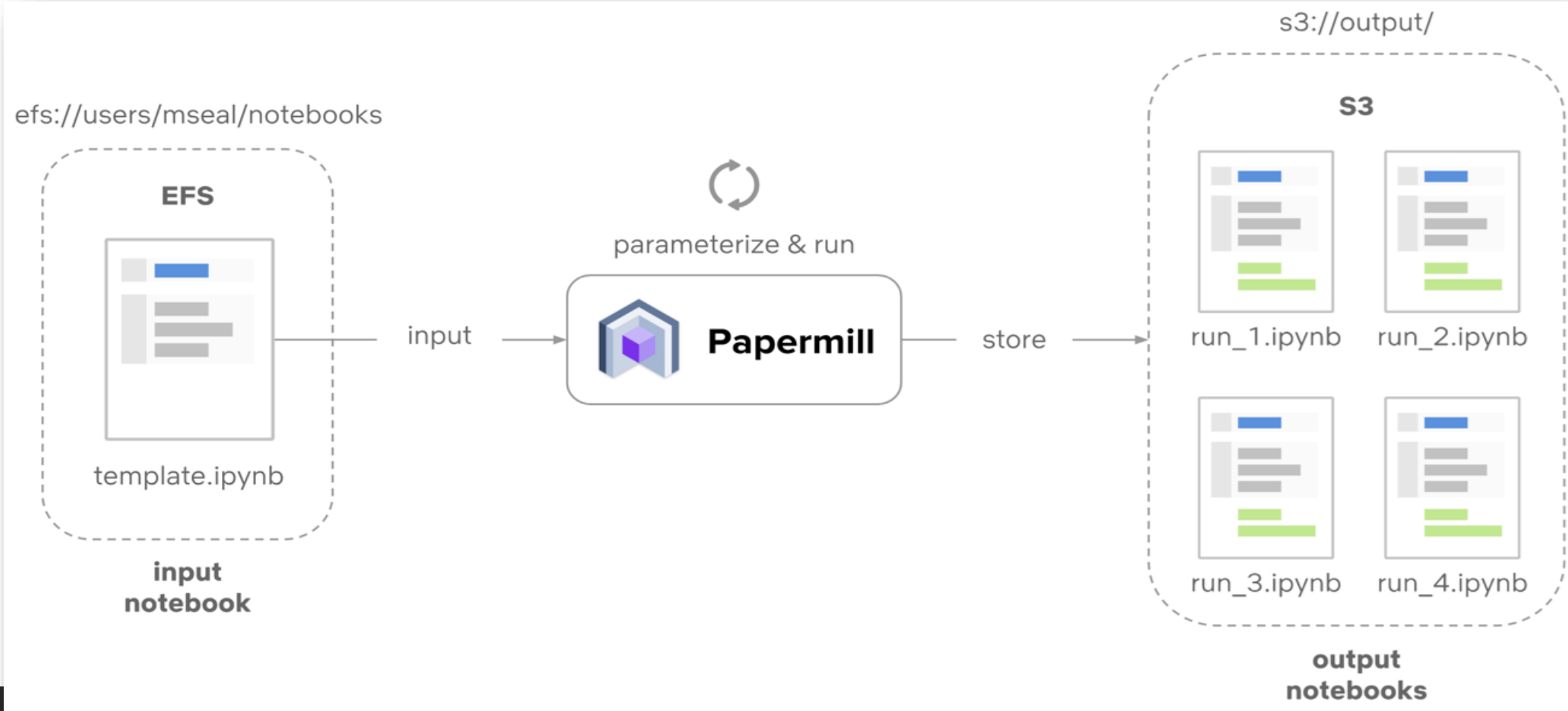
Putting-it together – The Principles



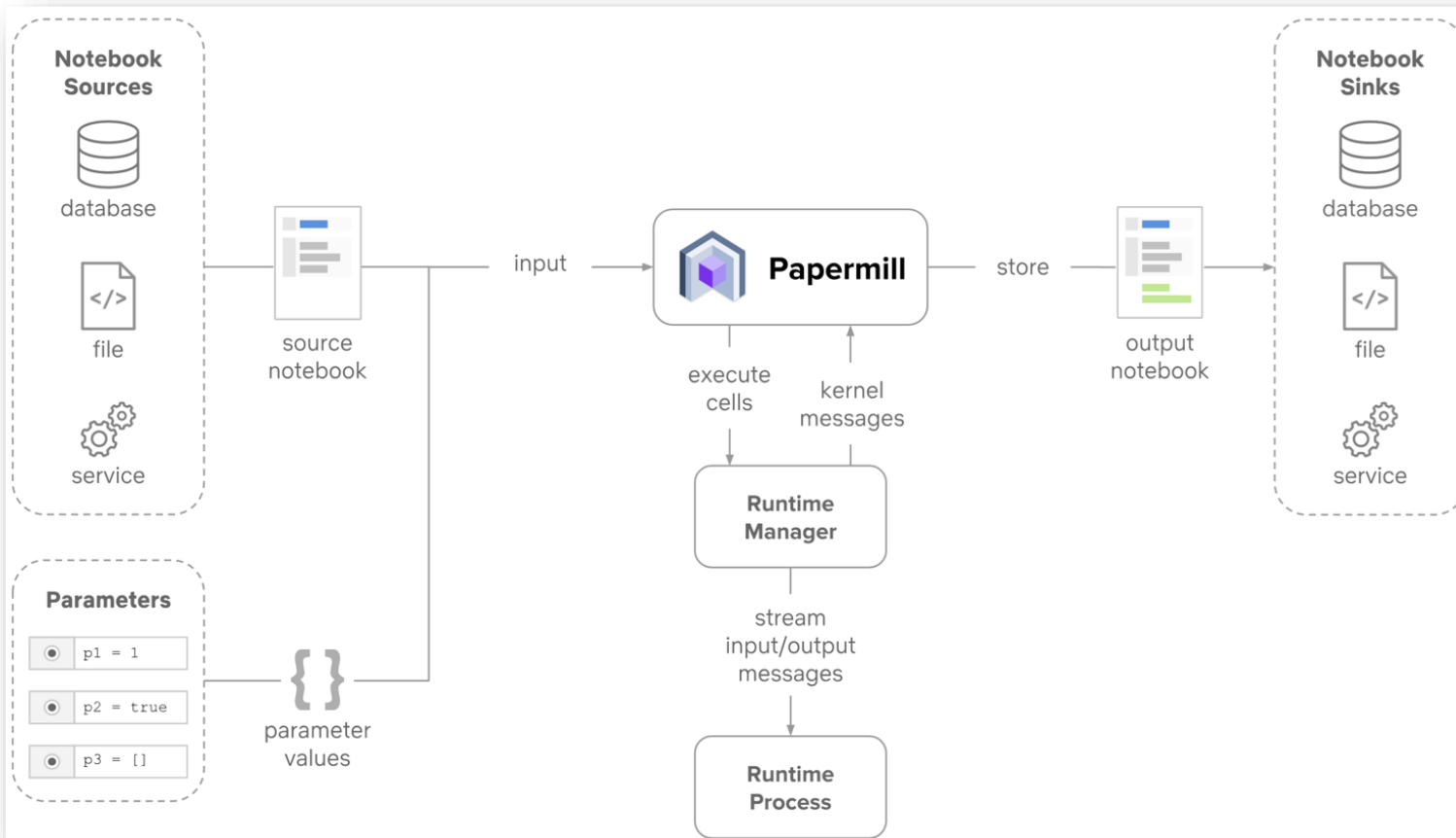
1. Keep a standard project structure and gitflow.
2. Refactor oft-repeated functions into Python modules.
3. Ensure that your notebook runs from top-to-bottom.
4. For data pipelines, use papermill (et al..) and configure your notebook to take advantage of it.



Papermill



How it works



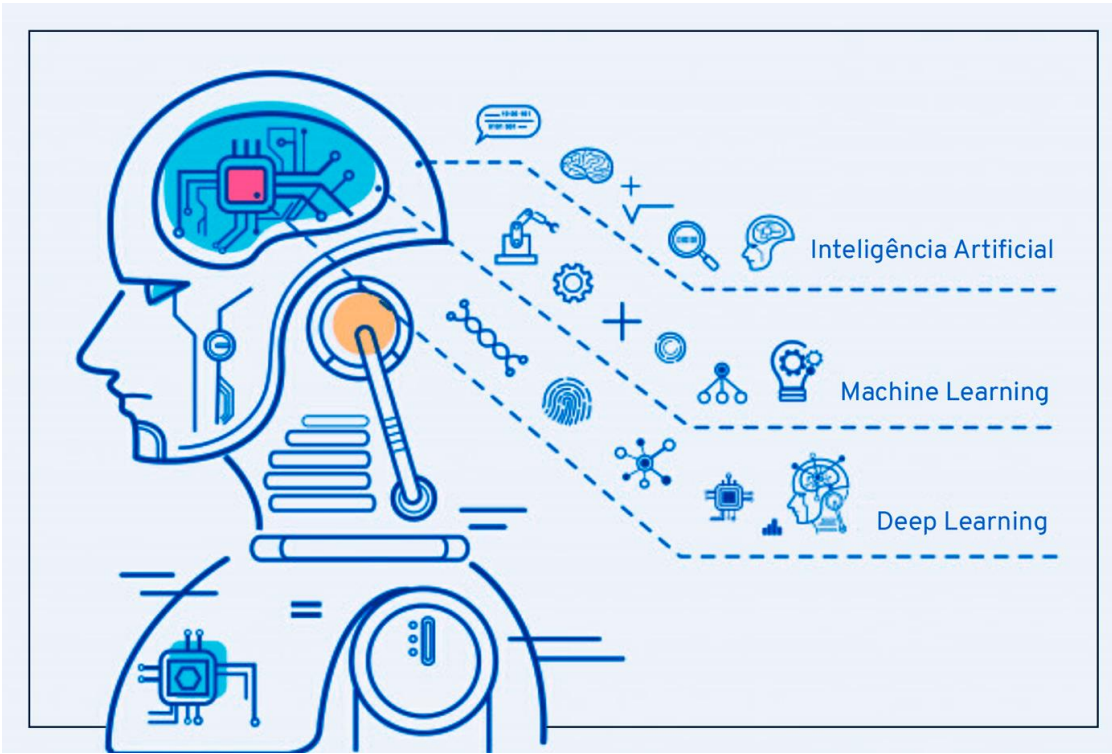
Reads from a source

Injects a parameters cell to the JSON document

Launches a runtime manager which runs the notebook kernel and collects messages.

Outputs to a sink





Hands on...



Turn a Git repo into a collection of interactive
notebooks

Have a repository full of Jupyter notebooks? With Binder, open those notebooks in an executable environment, making your code immediately reproducible by anyone, anywhere.

NOTEBOOK:

MACHINE LEARNING



References

<https://towardsdatascience.com/workflow-tools-for-model-pipelines-45030a93e9e0>

<https://elifesciences.org/labs/d42fe2b9/integrating-binder-and-stencila-the-building-blocks-to-increased-open-communication-and-transparency>

<https://zenodo.org/>

<https://mybinder.org/>

<https://stenci.la/>

<https://www.mysciencework.com/>

