How to Use Jupyter Notebook: A Beginner’s Tutorial

dataquest.io/blog/jupyter-notebook-tutorial/

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What is Jupyter Notebook?

The Jupyter Notebook is an incredibly powerful tool for interactively developing and presenting data science projects. This article will walk you through how to use Jupyter Notebooks for data science projects and how to set it up on your local machine.

First, though: **what is a “notebook”?**

A notebook integrates code and its output into a single document that combines visualizations, narrative text, mathematical equations, and other rich media. In other words: it's a single document where you can run code, display the output, and also add explanations, formulas, charts, and make your work more transparent, understandable, repeatable, and shareable.

Using Notebooks is now a major part of the data science workflow at companies across the globe. If your goal is to work with data, using a Notebook will speed up your workflow and make it easier to communicate and share your results.

Best of all, as part of the open source Project Jupyter, Jupyter Notebooks are completely free. You can download the software on its own, or as part of the Anaconda data science toolkit.

Although it is possible to use many different programming languages in Jupyter Notebooks, this article will focus on Python, as it is the most common use case. (Among R users, R Studio tends to be a more popular choice).

How to Follow This Tutorial

To get the most out of this tutorial you should be familiar with programming — Python and pandas specifically. That said, if you have experience with another language, the Python in this article shouldn’t be too cryptic, and will still help you get Jupyter Notebooks set up locally.

Jupyter Notebooks can also act as a flexible platform for getting to grips with pandas and even Python, as will become apparent in this tutorial.

We will:

- Cover the basics of installing Jupyter and creating your first notebook
- Delve deeper and learn all the important terminology

- Explore how easily notebooks can be shared and published online.

(In fact, this article was written as a Jupyter Notebook! It's published here in read-only form, but this is a good example of how versatile notebooks can be. In fact, most of our programming tutorials and even our Python courses were created using Jupyter Notebooks).

Example Data Analysis in a Jupyter Notebook

First, we will walk through setup and a sample analysis to answer a real-life question. This will demonstrate how the flow of a notebook makes data science tasks more intuitive for us as we work, and for others once it's time to share our work.

So, let's say you're a data analyst and you've been tasked with finding out how the profits of the largest companies in the US changed historically. You find a data set of Fortune 500 companies spanning over 50 years since the list's first publication in 1955, put together from Fortune's public archive. We've gone ahead and created a CSV of the data you can use here.

As we shall demonstrate, Jupyter Notebooks are perfectly suited for this investigation. First, let's go ahead and install Jupyter.

Installation

The easiest way for a beginner to get started with Jupyter Notebooks is by installing Anaconda.

Anaconda is the most widely used Python distribution for data science and comes pre-loaded with all the most popular libraries and tools.

Some of the biggest Python libraries included in Anaconda include NumPy, pandas, and Matplotlib, though the full 1000+ list is exhaustive.

Anaconda thus lets us hit the ground running with a fully stocked data science workshop without the hassle of managing countless installations or worrying about dependencies and OS-specific (read: Windows-specific) installation issues.

To get Anaconda, simply:

1. Download the latest version of Anaconda for Python 3.8.
2. Install Anaconda by following the instructions on the download page and/or in the executable.

If you are a more advanced user with Python already installed and prefer to manage your packages manually, you can just use pip:

```
pip3 install jupyter
```

Creating Your First Notebook

In this section, we're going to learn to run and save notebooks, familiarize ourselves with their structure, and understand the interface. We'll become intimate with some core terminology that will steer you towards a practical understanding of how to use Jupyter Notebooks by yourself and set us up for the next section, which walks through an example data analysis and brings everything we learn here to life.

Running Jupyter

On Windows, you can run Jupyter via the shortcut Anaconda adds to your start menu, which will open a new tab in your default web browser that should look something like the following screenshot.

This isn't a notebook just yet, but don't panic! There's not much to it. This is the Notebook Dashboard, specifically designed for managing your Jupyter Notebooks. Think of it as the launchpad for exploring, editing and creating your notebooks.

Be aware that the dashboard will give you access only to the files and sub-folders contained within Jupyter's start-up directory (i.e., where Jupyter or Anaconda is installed). However, the start-up directory can be changed.

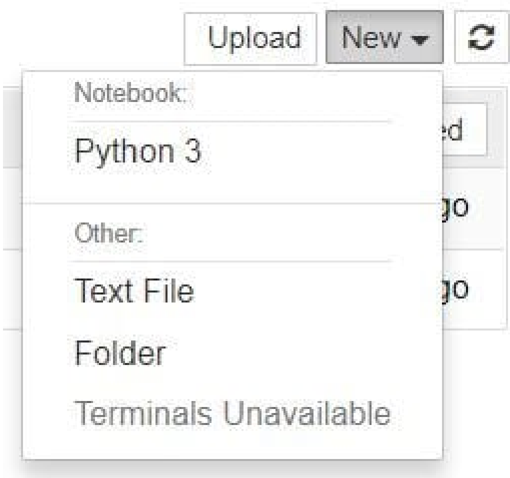
It is also possible to start the dashboard on any system via the command prompt (or terminal on Unix systems) by entering the command `jupyter notebook`; in this case, the current working directory will be the start-up directory.

With Jupyter Notebook open in your browser, you may have noticed that the URL for the dashboard is something like `https://localhost:8888/tree`. Localhost is not a website, but indicates that the content is being served from your *local* machine: your own computer.

Jupyter's Notebooks and dashboard are web apps, and Jupyter starts up a local Python server to serve these apps to your web browser, making it essentially platform-independent and opening the door to easier sharing on the web.

(If you don't understand this yet, don't worry — the important point is just that although Jupyter Notebooks opens in your browser, it's being hosted and run on your local machine. Your notebooks aren't actually on the web until you decide to share them.)

The dashboard's interface is mostly self-explanatory — though we will come back to it briefly later. So what are we waiting for? Browse to the folder in which you would like to create your first notebook, click the "New" drop-down button in the top-right and select "Python 3":



Hey presto, here we are! Your first Jupyter Notebook will open in new tab — each notebook uses its own tab because you can open multiple notebooks simultaneously.

If you switch back to the dashboard, you will see the new file `Untitled.ipynb` and you should see some green text that tells you your notebook is running.

What is an ipynb File?

The short answer: each `.ipynb` file is one notebook, so each time you create a new notebook, a new `.ipynb` file will be created.

The longer answer: Each `.ipynb` file is a text file that describes the contents of your notebook in a format called JSON. Each cell and its contents, including image attachments that have been converted into strings of text, is listed therein along with some metadata.

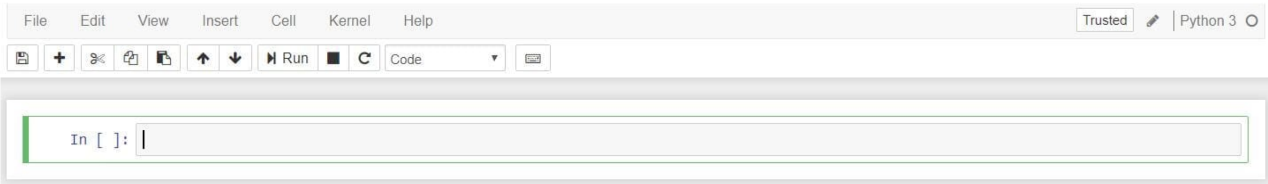
You can edit this yourself — if you know what you are doing! — by selecting "Edit > Edit Notebook Metadata" from the menu bar in the notebook. You can also view the contents of your notebook files by selecting "Edit" from the controls on the dashboard

However, the key word there is *can.* In most cases, there's no reason you should ever need to edit your notebook metadata manually.

The Notebook Interface

Now that you have an open notebook in front of you, its interface will hopefully not look entirely alien. After all, Jupyter is essentially just an advanced word processor.

Why not take a look around? Check out the menus to get a feel for it, especially take a few moments to scroll down the list of commands in the command palette, which is the small button with the keyboard icon (or `Ctrl + Shift + P`).



There are two fairly prominent terms that you should notice, which are probably new to you: *cells* and *kernels* are key both to understanding Jupyter and to what makes it more than just a word processor. Fortunately, these concepts are not difficult to understand.

- A **kernel** is a “computational engine” that executes the code contained in a notebook document.
- A **cell** is a container for text to be displayed in the notebook or code to be executed by the notebook’s kernel.

Cells

We’ll return to kernels a little later, but first let’s come to grips with cells. Cells form the body of a notebook. In the screenshot of a new notebook in the section above, that box with the green outline is an empty cell. There are two main cell types that we will cover:

- A **code cell** contains code to be executed in the kernel. When the code is run, the notebook displays the output below the code cell that generated it.
- A **Markdown cell** contains text formatted using Markdown and displays its output in-place when the Markdown cell is run.

The first cell in a new notebook is always a code cell.

Let’s test it out with a classic hello world example: Type `print('Hello World!')` into the cell and click the run button 

in the toolbar above or press `Ctrl + Enter`.

The result should look like this:

```
print('Hello World!')
```

```
Hello World!
```

When we run the cell, its output is displayed below and the label to its left will have changed from `In [ ]` to `In [1]`.

The output of a code cell also forms part of the document, which is why you can see it in this article. You can always tell the difference between code and Markdown cells because code cells have that label on the left and Markdown cells do not.

The “In” part of the label is simply short for “Input,” while the label number indicates *when* the cell was executed on the kernel — in this case the cell was executed first.

Run the cell again and the label will change to `In [2]` because now the cell was the second to be run on the kernel. It will become clearer why this is so useful later on when we take a closer look at kernels.

From the menu bar, click *Insert* and select *Insert Cell Below* to create a new code cell underneath your first and try out the following code to see what happens. Do you notice anything different?

```
import time
time.sleep(3)
```

This cell doesn’t produce any output, but it does take three seconds to execute. Notice how Jupyter signifies when the cell is currently running by changing its label to `In [*]`.

In general, the output of a cell comes from any text data specifically printed during the cell's execution, as well as the value of the last line in the cell, be it a lone variable, a function call, or something else. For example:

```
def say_hello(recipient):
    return 'Hello, {}!'.format(recipient)

say_hello('Tim')
```

```
'Hello, Tim!'
```

You’ll find yourself using this almost constantly in your own projects, and we’ll see more of it later on.

Keyboard Shortcuts

One final thing you may have observed when running your cells is that their border turns blue, whereas it was green while you were editing. In a Jupyter Notebook, there is always one “active” cell highlighted with a border whose color denotes its current mode:

- **Green outline** — cell is in "edit mode"
- **Blue outline** — cell is in "command mode"

So what can we do to a cell when it's in command mode? So far, we have seen how to run a cell with `Ctrl + Enter`, but there are plenty of other commands we can use. The best way to use them is with keyboard shortcuts

Keyboard shortcuts are a very popular aspect of the Jupyter environment because they facilitate a speedy cell-based workflow. Many of these are actions you can carry out on the active cell when it’s in command mode.

Below, you'll find a list of some of Jupyter's keyboard shortcuts. You don't need to memorize them all immediately, but this list should give you a good idea of what's possible.

- Toggle between edit and command mode with `Esc` and `Enter`, respectively.
- Once in command mode:
  - Scroll up and down your cells with your `Up` and `Down` keys.
  - Press `A` or `B` to insert a new cell above or below the active cell.
  - `M` will transform the active cell to a Markdown cell.
  - `Y` will set the active cell to a code cell.
  - `D + D` (`D` twice) will delete the active cell.
  - `Z` will undo cell deletion.
  - Hold `Shift` and press `Up` or `Down` to select multiple cells at once. With multiple cells selected, `Shift + M` will merge your selection.
- `Ctrl + Shift + -`, in edit mode, will split the active cell at the cursor.
- You can also click and `Shift + Click` in the margin to the left of your cells to select them.

Go ahead and try these out in your own notebook. Once you're ready, create a new Markdown cell and we'll learn how to format the text in our notebooks.

Markdown

Markdown is a lightweight, easy to learn markup language for formatting plain text. Its syntax has a one-to-one correspondence with HTML tags, so some prior knowledge here would be helpful but is definitely not a prerequisite.

Remember that this article was written in a Jupyter notebook, so all of the narrative text and images you have seen so far were achieved writing in Markdown. Let's cover the basics with a quick example:

````
# This is a level 1 heading

## This is a level 2 heading

This is some plain text that forms a paragraph. Add emphasis via **bold** and
__bold__, or *italic* and _italic_.

Paragraphs must be separated by an empty line.

* Sometimes we want to include lists.
* Which can be bulleted using asterisks.

1. Lists can also be numbered.
2. If we want an ordered list.

[It is possible to include hyperlinks](https://www.example.com)

Inline code uses single backticks: foo(), and code blocks use triple backticks:
```
bar()
```
Or can be indented by 4 spaces:

    foo()

And finally, adding images is easy: ![Alt text](https://www.example.com/image.jpg)
````

Here's how that Markdown would look once you run the cell to render it:

This is a level 1 heading

This is a level 2 heading

This is some plain text that forms a paragraph. Add emphasis via **bold** and **bold**, or *italic* and *italic*.

Paragraphs must be separated by an empty line.

- Sometimes we want to include lists.
- Which can be bulleted using asterisks.
- Lists can also be numbered.
- If we want an ordered list.

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Inline code uses single backticks: `foo()`, and code blocks use triple backticks:

```
bar()
```

Or can be indented by 4 spaces:

```
foo()
```

And finally, adding images is easy:
Alt text

(Note that the alt text for the image is displayed here because we didn't actually use a valid image URL in our example)

When attaching images, you have three options:

- Use a URL to an image on the web.
- Use a local URL to an image that you will be keeping alongside your notebook, such as in the same git repo.
- Add an attachment via "Edit > Insert Image"; this will convert the image into a string and store it inside your notebook `.ipynb` file. Note that this will make your `.ipynb` file much larger!

There is plenty more to Markdown, especially around hyperlinking, and it's also possible to simply include plain HTML. Once you find yourself pushing the limits of the basics above, you can refer to the official guide from Markdown's creator, John Gruber, on his website.

Kernels

Behind every notebook runs a kernel. When you run a code cell, that code is executed within the kernel. Any output is returned back to the cell to be displayed. The kernel's state persists over time and between cells — it pertains to the document as a whole and not individual cells.

For example, if you import libraries or declare variables in one cell, they will be available in another. Let's try this out to get a feel for it. First, we'll import a Python package and define a function:

```
import numpy as np
def square(x):
    return x * x
```

Once we've executed the cell above, we can reference `np` and `square` in any other cell.

```
x = np.random.randint(1, 10)
y = square(x)
print('%d squared is %d' % (x, y))
```

```
1 squared is 1
```

This will work regardless of the order of the cells in your notebook. As long as a cell has been run, any variables you declared or libraries you imported will be available in other cells.

You can try it yourself, let's print out our variables again.

```
print('Is %d squared %d?' % (x, y))
```

```
Is 1 squared 1?
```

No surprises here! But what happens if we change the value of `y?`

```
y = 10
print('Is %d squared is %d?' % (x, y))
```

If we run the cell above, what do you think would happen?

We will get an output like: `Is 4 squared 10?`. This is because once we've run the `y = 10` code cell, `y` is no longer equal to the square of x in the kernel.

Most of the time when you create a notebook, the flow will be top-to-bottom. But it's common to go back to make changes. When we do need to make changes to an earlier cell, the order of execution we can see on the left of each cell, such as `In [6]`, can help us diagnose problems by seeing what order the cells have run in.

And if we ever wish to reset things, there are several incredibly useful options from the Kernel menu:

- Restart: restarts the kernel, thus clearing all the variables etc that were defined.
- Restart & Clear Output: same as above but will also wipe the output displayed below your code cells.
- Restart & Run All: same as above but will also run all your cells in order from first to last.

If your kernel is ever stuck on a computation and you wish to stop it, you can choose the Interrupt option.

Choosing a Kernel

You may have noticed that Jupyter gives you the option to change kernel, and in fact there are many different options to choose from. Back when you created a new notebook from the dashboard by selecting a Python version, you were actually choosing which kernel to use.

There kernels for different versions of Python, and also for over 100 languages including Java, C, and even Fortran. Data scientists may be particularly interested in the kernels for R and Julia, as well as both imatlab and the Calysto MATLAB Kernel for Matlab.

The SoS kernel provides multi-language support within a single notebook.

Each kernel has its own installation instructions, but will likely require you to run some commands on your computer.

Example Analysis

Now we've looked at *what* a Jupyter Notebook is, it's time to look at *how* they're used in practice, which should give us clearer understanding of *why* they are so popular.

It's finally time to get started with that Fortune 500 data set mentioned earlier. Remember, our goal is to find out **how the profits of the largest companies in the US changed historically**.

It’s worth noting that everyone will develop their own preferences and style, but the general principles still apply. You can follow along with this section in your own notebook if you wish, or use this as a guide to creating your own approach.

Naming Your Notebooks

Before you start writing your project, you’ll probably want to give it a meaningful name. file name `Untitled` in the upper left of the screen to enter a new file name, and hit the Save icon (which looks like a floppy disk) below it to save.

Note that closing the notebook tab in your browser will **not** “close” your notebook in the way closing a document in a traditional application will. The notebook’s kernel will continue to run in the background and needs to be shut down before it is truly “closed” — though this is pretty handy if you accidentally close your tab or browser!

If the kernel is shut down, you can close the tab without worrying about whether it is still running or not.

The easiest way to do this is to select “File > Close and Halt” from the notebook menu. However, you can also shutdown the kernel either by going to “Kernel > Shutdown” from within the notebook app or by selecting the notebook in the dashboard and clicking “Shutdown” (see image below).

Setup

It’s common to start off with a code cell specifically for imports and setup, so that if you choose to add or change anything, you can simply edit and re-run the cell without causing any side-effects.

```
%matplotlib inline
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns sns.set(style="darkgrid")
```

We'll import pandas to work with our data, Matplotlib to plot charts, and Seaborn to make our charts prettier. It’s also common to import NumPy but in this case, pandas imports it for us.

That first line isn’t a Python command, but uses something called a line magic to instruct Jupyter to capture Matplotlib plots and render them in the cell output. We'll talk a bit more about line magics later, and they're also covered in our advanced Jupyter Notebooks tutorial.

For now, let's go ahead and load our data.

```
df = pd.read_csv('fortune500.csv')
```

It's sensible to also do this in a single cell, in case we need to reload it at any point.

Save and Checkpoint

Now we've got started, it's best practice to save regularly. Pressing `Ctrl + S` will save our notebook by calling the "Save and Checkpoint" command, but what is this checkpoint thing?

Every time we create a new notebook, a checkpoint file is created along with the notebook file. It is located within a hidden subdirectory of your save location called `.ipynb_checkpoints` and is also a `.ipynb` file.

By default, Jupyter will autosave your notebook every 120 seconds to this checkpoint file without altering your primary notebook file. When you "Save and Checkpoint," both the notebook and checkpoint files are updated. Hence, the checkpoint enables you to recover your unsaved work in the event of an unexpected issue.

You can revert to the checkpoint from the menu via "File > Revert to Checkpoint."

Investigating Our Data Set

Now we're really rolling! Our notebook is safely saved and we've loaded our data set `df` into the most-used pandas data structure, which is called a `DataFrame` and basically looks like a table. What does ours look like?

```
df.head()
```

Year	Rank	Company	Revenue (in millions)	Profit (in millions)	
0	1955	1	General Motors	9823.5	806
1	1955	2	Exxon Mobil	5661.4	584.8
2	1955	3	U.S. Steel	3250.4	195.4
3	1955	4	General Electric	2959.1	212.6
4	1955	5	Esmark	2510.8	19.1

```
df.tail()
```

Year	Rank	Company	Revenue (in millions)	Profit (in millions)	
25495	2005	496	Wm. Wrigley Jr.	3648.6	493

Year	Rank	Company	Revenue (in millions)	Profit (in millions)	
25496	2005	497	Peabody Energy	3631.6	175.4
25497	2005	498	Wendy’s International	3630.4	57.8
25498	2005	499	Kindred Healthcare	3616.6	70.6
25499	2005	500	Cincinnati Financial	3614.0	584

Looking good. We have the columns we need, and each row corresponds to a single company in a single year.

Let’s just rename those columns so we can refer to them later.

```
df.columns = ['year', 'rank', 'company', 'revenue', 'profit']
```

Next, we need to explore our data set. Is it complete? Did pandas read it as expected? Are any values missing?

```
len(df)
```

```
25500
```

Okay, that looks good — that’s 500 rows for every year from 1955 to 2005, inclusive.

Let’s check whether our data set has been imported as we would expect. A simple check is to see if the data types (or dtypes) have been correctly interpreted.

```
df.dtypes
```

```
year int64 rank int64 company object revenue float64 profit object dtype: object
```

Uh oh. It looks like there’s something wrong with the profits column — we would expect it to be a `float64` like the revenue column. This indicates that it probably contains some non-integer values, so let’s take a look.

```
non_numberic_profits = df.profit.str.contains('[^0-9.-]')
df.loc[non_numberic_profits].head()
```

year	rank	company	revenue	profit	
228	1955	229	Norton	135.0	N.A.
290	1955	291	Schlitz Brewing	100.0	N.A.
294	1955	295	Pacific Vegetable Oil	97.9	N.A.
296	1955	297	Liebmann Breweries	96.0	N.A.
352	1955	353	Minneapolis-Moline	77.4	N.A.

Just as we suspected! Some of the values are strings, which have been used to indicate missing data. Are there any other values that have crept in?

```
set(df.profit[non_numberic_profits])
```

```
{'N.A.'}
```

That makes it easy to interpret, but what should we do? Well, that depends how many values are missing.

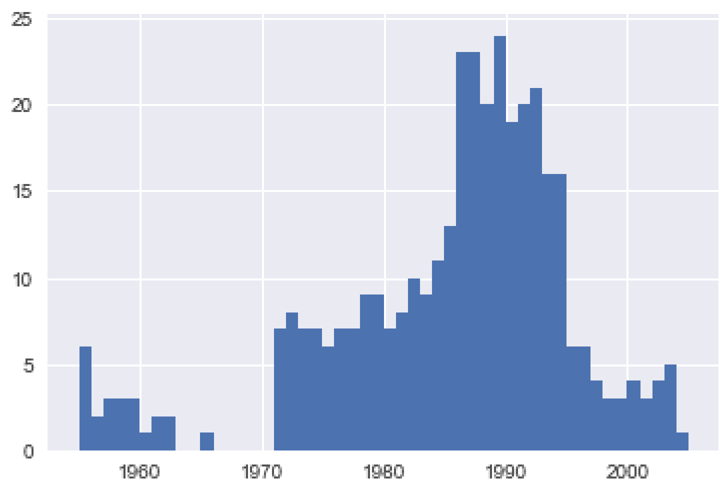
```
len(df.profit[non_numberic_profits])
```

```
369
```

It's a small fraction of our data set, though not completely inconsequential as it is still around 1.5%.

If rows containing `N.A.` are, roughly, uniformly distributed over the years, the easiest solution would just be to remove them. So let's have a quick look at the distribution.

```
bin_sizes, _, _ = plt.hist(df.year[non_numberic_profits], bins=range(1955, 2006))
```



At a glance, we can see that the most invalid values in a single year is fewer than 25, and as there are 500 data points per year, removing these values would account for less than 4% of the data for the worst years. Indeed, other than a surge around the 90s, most years have fewer than half the missing values of the peak.

For our purposes, let's say this is acceptable and go ahead and remove these rows.

```
df = df.loc[~non_numberic_profits]
df.profit = df.profit.apply(pd.to_numeric)
```

We should check that worked.

```
len(df)
```

```
25131
```

```
df.dtypes
```

```
year int64 rank int64 company object revenue float64 profit float64 dtype: object
```

Great! We have finished our data set setup.

If we were going to present your notebook as a report, we could get rid of the investigatory cells we created, which are included here as a demonstration of the flow of working with notebooks, and merge relevant cells (see the Advanced Functionality section below for more on this) to create a single data set setup cell.

This would mean that if we ever mess up our data set elsewhere, we can just rerun the setup cell to restore it.

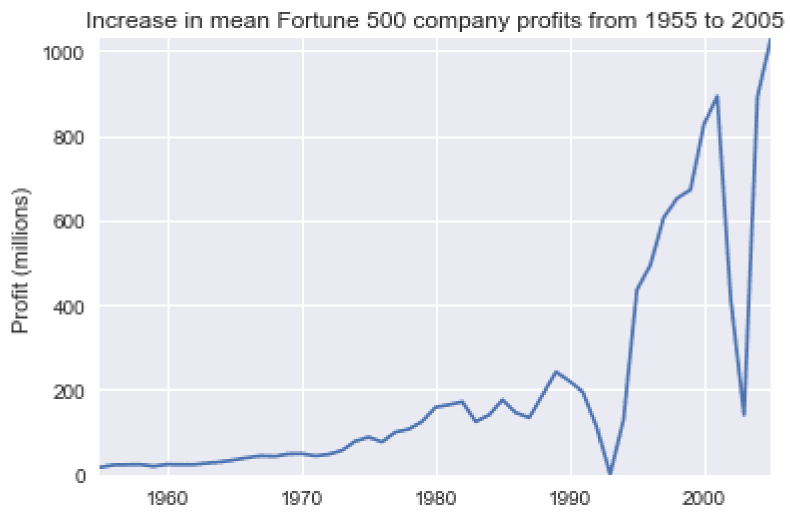
Plotting with matplotlib

Next, we can get to addressing the question at hand by plotting the average profit by year. We might as well plot the revenue as well, so first we can define some variables and a method to reduce our code.

```
group_by_year = df.loc[:, ['year', 'revenue', 'profit']].groupby('year')
avgs = group_by_year.mean()
x = avgs.index
y1 = avgs.profit
def plot(x, y, ax, title, y_label):
    ax.set_title(title)
    ax.set_ylabel(y_label)
    ax.plot(x, y)
    ax.margins(x=0, y=0)
```

Now let's plot!

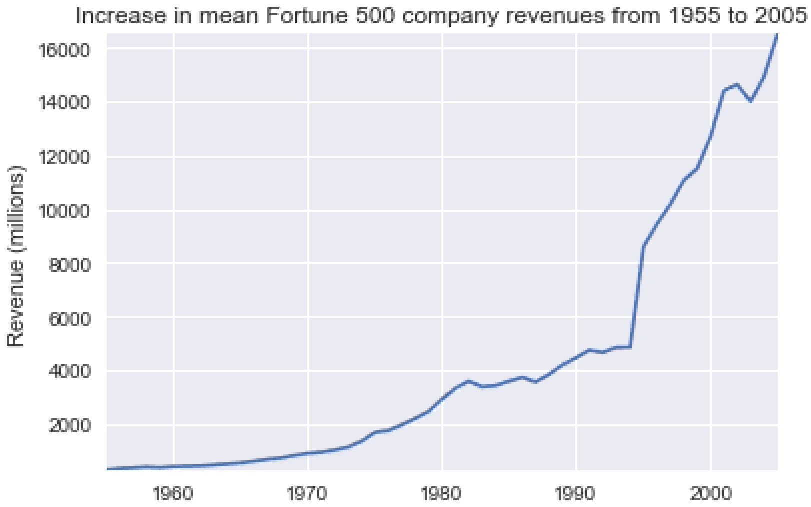
```
fig, ax = plt.subplots()
plot(x, y1, ax, 'Increase in mean Fortune 500 company profits from 1955 to 2005',
'Profit (millions)')
```



Wow, that looks like an exponential, but it's got some huge dips. They must correspond to the early 1990s recession and the dot-com bubble. It's pretty interesting to see that in the data. But how come profits recovered to even higher levels post each recession?

Maybe the revenues can tell us more.

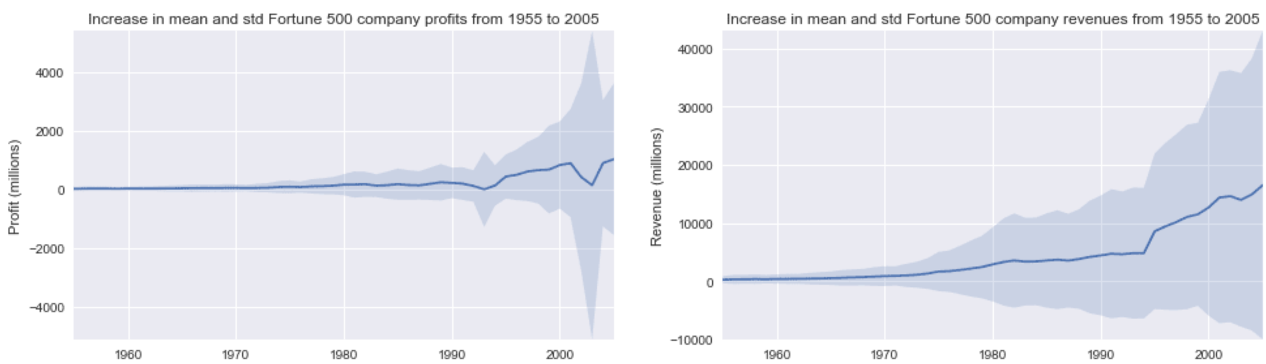
```
y2 = avgs.revenue
fig, ax = plt.subplots()
plot(x, y2, ax, 'Increase in mean Fortune 500 company revenues from 1955 to 2005',
'Revenue (millions)')
```



That adds another side to the story. Revenues were not as badly hit — that's some great accounting work from the finance departments.

With a little help from Stack Overflow, we can superimpose these plots with +/- their standard deviations.

```
def plot_with_std(x, y, stds, ax, title, y_label):
    ax.fill_between(x, y - stds, y + stds, alpha=0.2)
    plot(x, y, ax, title, y_label)
fig, (ax1, ax2) = plt.subplots(ncols=2)
title = 'Increase in mean and std Fortune 500 company %s from 1955 to 2005'
stds1 = group_by_year.std().profit.values
stds2 = group_by_year.std().revenue.values
plot_with_std(x, y1.values, stds1, ax1, title % 'profits', 'Profit (millions)')
plot_with_std(x, y2.values, stds2, ax2, title % 'revenues', 'Revenue (millions)')
fig.set_size_inches(14, 4)
fig.tight_layout()
```



That's staggering, the standard deviations are huge! Some Fortune 500 companies make billions while others lose billions, and the risk has increased along with rising profits over the years.

Perhaps some companies perform better than others; are the profits of the top 10% more or less volatile than the bottom 10%?

There are plenty of questions that we could look into next, and it's easy to see how the flow of working in a notebook can match one's own thought process. For the purposes of this tutorial, we'll stop our analysis here, but feel free to continue digging into the data on your own!

This flow helped us to easily investigate our data set in one place without context switching between applications, and our work is immediately shareable and reproducible. If we wished to create a more concise report for a particular audience, we could quickly refactor our work by merging cells and removing intermediary code.

Sharing Your Notebooks

When people talk about sharing their notebooks, there are generally two paradigms they may be considering.

Most often, individuals share the end-result of their work, much like this article itself, which means sharing non-interactive, pre-rendered versions of their notebooks. However, it is also possible to collaborate on notebooks with the aid of version control systems such as Git or online platforms like Google Colab.

Before You Share

A shared notebook will appear exactly in the state it was in when you export or save it, including the output of any code cells. Therefore, to ensure that your notebook is share-ready, so to speak, there are a few steps you should take before sharing:

1. Click "Cell > All Output > Clear"
2. Click "Kernel > Restart & Run All"
3. Wait for your code cells to finish executing and check ran as expected

This will ensure your notebooks don't contain intermediary output, have a stale state, and execute in order at the time of sharing.

Exporting Your Notebooks

Jupyter has built-in support for exporting to HTML and PDF as well as several other formats, which you can find from the menu under "File > Download As."

If you wish to share your notebooks with a small private group, this functionality may well be all you need. Indeed, as many researchers in academic institutions are given some public or internal webspace, and because you can export a notebook to an HTML file, Jupyter Notebooks can be an especially convenient way for researchers to share their results with their peers.

But if sharing exported files doesn't cut it for you, there are also some immensely popular methods of sharing `.ipynb` files more directly on the web.

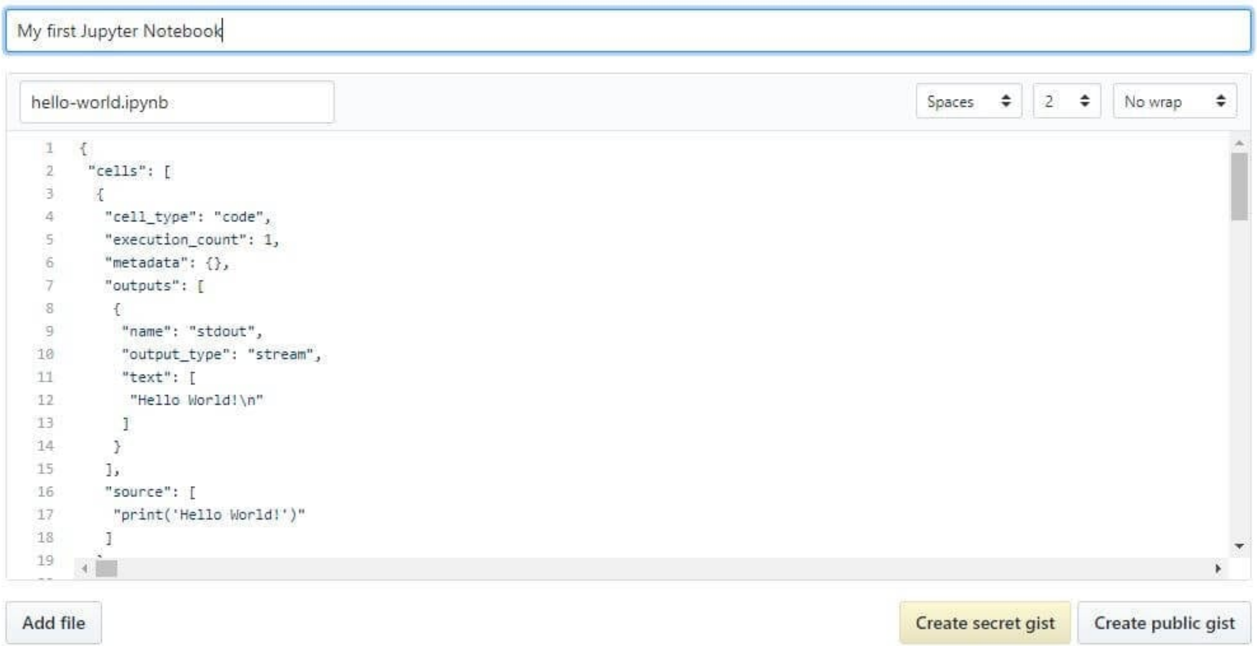
GitHub

With the number of public notebooks on GitHub exceeding 1.8 million by early 2018, it is surely the most popular independent platform for sharing Jupyter projects with the world. GitHub has integrated support for rendering `.ipynb` files directly both in repositories and gists on its website. If you aren't already aware, GitHub is a code hosting platform for version control and collaboration for repositories created with Git. You'll need an account to use their services, but standard accounts are free.

Once you have a GitHub account, the easiest way to share a notebook on GitHub doesn't actually require Git at all. Since 2008, GitHub has provided its Gist service for hosting and sharing code snippets, which each get their own repository. To share a notebook using Gists:

1. Sign in and navigate to gist.github.com.
2. Open your `.ipynb` file in a text editor, select all and copy the JSON inside.
3. Paste the notebook JSON into the gist.
4. Give your Gist a filename, remembering to add `.iypnb` or this will not work.
5. Click either "Create secret gist" or "Create public gist."

This should look something like the following:



If you created a public Gist, you will now be able to share its URL with anyone, and others will be able to fork and clone your work.

Creating your own Git repository and sharing this on GitHub is beyond the scope of this tutorial, but GitHub provides plenty of guides for you to get started on your own.

An extra tip for those using git is to add an exception to your `.gitignore` for those hidden `.ipynb_checkpoints` directories Jupyter creates, so as not to commit checkpoint files unnecessarily to your repo.

Nbviewer

Having grown to render hundreds of thousands of notebooks every week by 2015, NBViewer is the most popular notebook renderer on the web. If you already have somewhere to host your Jupyter Notebooks online, be it GitHub or elsewhere, NBViewer will render your notebook and provide a shareable URL along with it. Provided as a free service as part of Project Jupyter, it is available at nbviewer.jupyter.org.

Initially developed before GitHub's Jupyter Notebook integration, NBViewer allows anyone to enter a URL, Gist ID, or GitHub username/repo/file and it will render the notebook as a webpage. A Gist's ID is the unique number at the end of its URL; for example, the string of characters after the last backslash in `https://gist.github.com/username/50896401c23e0bf417e89cd57e89e1de`. If you enter a GitHub username or username/repo, you will see a minimal file browser that lets you explore a user's repos and their contents.

The URL NBViewer displays when displaying a notebook is a constant based on the URL of the notebook it is rendering, so you can share this with anyone and it will work as long as the original files remain online — NBViewer doesn't cache files for very long.

If you don't like Nbviewer, there are other similar options — here's a thread with a few to consider from our community.

Extras: Jupyter Notebook Extensions

We've already covered everything you need to get rolling in Jupyter Notebooks.

What Are Extensions?

Extensions are precisely what they sound like — additional features that extend Jupyter Notebooks's functionality. While a base Jupyter Notebook can do an awful lot, extensions offer some additional features that may help with specific workflows, or that simply improve the user experience.

For example, one extension called "Table of Contents" generates a table of contents for your notebook, to make large notebooks easier to visualize and navigate around.

Another one, called Variable Inspector, will show you the value, type, size, and shape of every variable in your notebook for easy quick reference and debugging.

Another, called ExecuteTime, lets you know when and for how long each cell ran — this can be particularly convenient if you're trying to speed up a snippet of your code.

These are just the tip of the iceberg; there are many extensions available.

Where Can You Get Extensions?

To get the extensions, you need to install Nbextensions. You can do this using pip and the command line. If you have Anaconda, it may be better to do this through Anaconda Prompt rather than the regular command line.

Close Jupyter Notebooks, open Anaconda Prompt, and run the following command: `pip install jupyter_contrib_nbextensions && jupyter contrib nbextension install`.

Once you've done that, start up a notebook and you should seen an Nbextensions tab. Clicking this tab will show you a list of available extensions. Simply tick the boxes for the extensions you want to enable, and you're off to the races!

Installing Extensions

Once Nbextensions itself has been installed, there's no need for additional installation of each extension. However, if you've already installed Nbextensons but aren't seeing the tab, you're not alone. This thread on Github details some common issues and solutions.

Extras: Line Magics in Jupyter

We mentioned magic commands earlier when we used `%matplotlib inline` to make Matplotlib charts render right in our notebook. There are many other magics we can use, too.

How to Use Magics in Jupyter

A good first step is to open a Jupyter Notebook, type `%lsmagic` into a cell, and run the cell. This will output a list of the available line magics and cell magics, and it will also tell you whether "automagic" is turned on.

- **Line magics** operate on a single line of a code cell
- **Cell magics** operate on the entire code cell in which they are called

If automagic is on, you can run a magic simply by typing it on its own line in a code cell, and running the cell. If it is off, you will need to put `%` before line magics and `%%` before cell magics to use them.

Many magics require additional input (much like a function requires an argument) to tell them how to operate. We'll look at an example in the next section, but you can see the documentation for any magic by running it with a question mark, like so:

```
%matplotlib?
```

When you run the above cell in a notebook, a lengthy docstring will pop up onscreen with details about how you can use the magic.

A Few Useful Magic Commands

We cover more in the advanced Jupyter tutorial, but here are a few to get you started:

Magic Command	What it does
%run	Runs an external script file as part of the cell being executed. For example, if **%run myscript.py** appears in a code cell, myscript.py will be executed by the kernel as part of that cell.
%timeit	Counts loops, measures and reports how long a code cell takes to execute.
%writefile	Save the contents of a cell to a file. For example, **%savefile myscript.py** would save the code cell as an external file called myscript.py.
%store	Save a variable for use in a different notebook.
%pwd	Print the directory path you're currently working in.
%%javascript	Runs the cell as JavaScript code.

There's plenty more where that came from. Hop into Jupyter Notebooks and start exploring using `%lsmagic`!

Final Thoughts

Starting from scratch, we have come to grips with the natural workflow of Jupyter Notebooks, delved into IPython's more advanced features, and finally learned how to share our work with friends, colleagues, and the world. And we accomplished all this from a notebook itself!

It should be clear how notebooks promote a productive working experience by reducing context switching and emulating a natural development of thoughts during a project. The power of using Jupyter Notebooks should also be evident, and we covered plenty of leads to get you started exploring more advanced features in your own projects.

If you'd like further inspiration for your own Notebooks, Jupyter has put together a gallery of interesting Jupyter Notebooks that you may find helpful and the Nbviewer homepage links to some really fancy examples of quality notebooks.

If you'd like to learn more about this topic, check out Dataquest's interactive Python Functions and Learn Jupyter Notebook course, and our Data Analyst in Python, and Data Scientist in Python paths that will help you become job-ready in around 6 months.

More Great Jupyter Notebooks Resources

- Advanced Jupyter Notebooks Tutorial – Now that you've mastered the basics, become a Jupyter Notebooks pro with this advanced tutorial!
- 28 Jupyter Notebooks Tips, Tricks, and Shortcuts – Make yourself into a power user and increase your efficiency with these tips and tricks!
- Guided Project – Install and Learn Jupyter Notebooks – Give yourself a great foundation working with Jupyter Notebooks by working through this interactive guided project that'll get you set up and teach you the ropes.

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