



Birla Institute of Technology and Science Pilani, Hyderabad Campus  
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# **BITS F464: Machine Learning**

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## **MACHINE LEARNING FRAMEWORKS**

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# Recap

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- Do you need ML to calculate Payroll?

ISRO's Chandrayaan-3 mission



23<sup>rd</sup> Aug, 2023



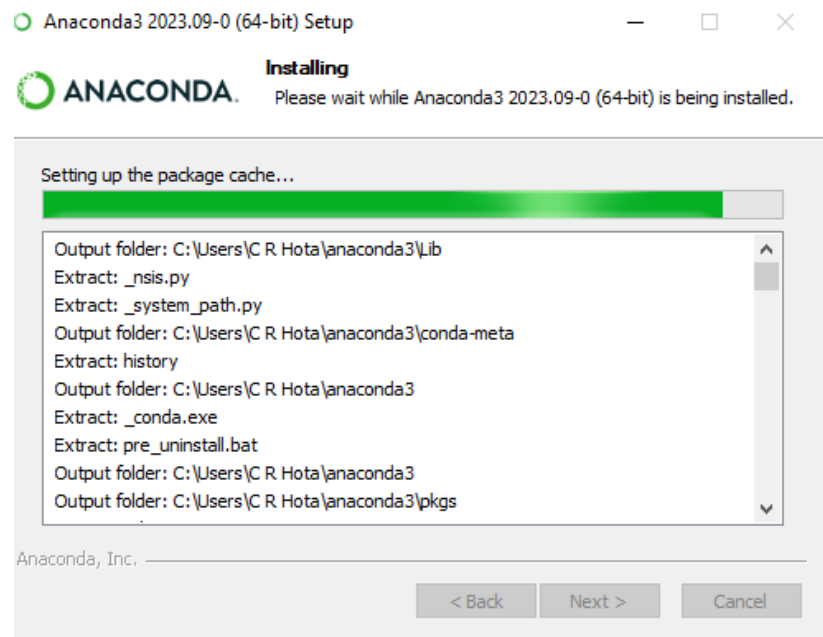
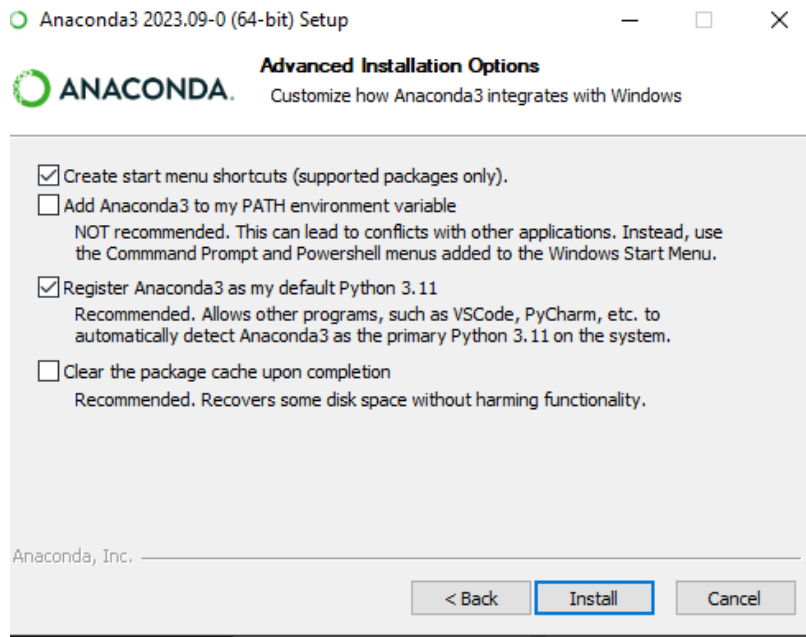
- Machine learning: Any change in a system that allows it to perform better the second time on repetition of the same task or on another task drawn from the same population.  
-- Herbert Simon, 1983
  - Clearly, being able to adapt & generalize are key to intelligence.
-



# ML Framework: Anaconda













- An ML framework is any tool, interface, or library that lets you develop ML models easily, without understanding the underlying algorithms.
- Anaconda is a distribution of the Python and R programming language for scientific computing suitable for ML.



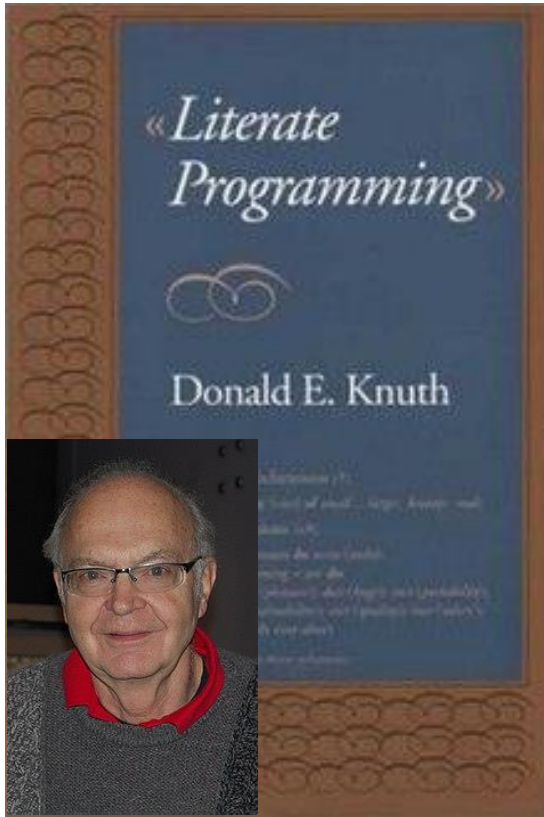
# Anaconda Navigator

Installed applications on base (root) Channels

 <b>Anaconda Notebooks</b> Cloud-hosted notebook service from Anaconda. Launch a preconfigured environment with hundreds of packages and store project files with persistent cloud storage. <a href="#">Launch</a>	 <b>CMD.exe Prompt</b> 0.1.1 Run a cmd.exe terminal with your current environment from Navigator activated <a href="#">Launch</a>	 <b>JupyterLab</b> 3.6.3 An extensible environment for interactive and reproducible computing, based on the Jupyter Notebook and Architecture. <a href="#">Launch</a>	 <b>Notebook</b> 6.5.4 Web-based, interactive computing notebook environment. Edit and run human-readable docs while describing the data analysis. <a href="#">Launch</a>	 <b>Powershell Prompt</b> 0.0.1 Run a Powershell terminal with your current environment from Navigator activated <a href="#">Launch</a>
 <b>Spyder</b> 5.4.3 Scientific PYTHON Development Environment. Powerful Python IDE with advanced editing, interactive testing, debugging and introspection features <a href="#">Launch</a>	 <b>Anaconda on AWS Graviton</b> Running your Anaconda workloads on AWS Graviton-based processors could provide up to 40% better price performance <a href="#">Launch</a>	 <b>DataLore</b> Kick-start your data science projects in seconds in a pre-configured environment. Enjoy coding assistance for Python, SQL, and R in Jupyter notebooks and benefit from no-code automations. Use DataLore online for free. <a href="#">Launch</a>	 <b>IBM watsonx</b> IBM watsonx is an enterprise-ready AI platform including a data store, model builder, and AI model management and monitoring. <a href="#">Launch</a>	 <b>ORACLE Cloud Infrastructure</b> Oracle Data Science Service OCI Data Science offers a machine learning platform to build, train, manage, and deploy your machine learning models on the cloud with your favorite open-source tools <a href="#">Launch</a>

# Notebook: Good Practices of Code Writing

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- Linear flow of execution.
- Little amount of code.
- Extract reusable code into a package.
- Clean it before storing it in a repository or sharing it with others.
- Develop your code as a story with text, small code fragments and images.

Source: Wiki

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# Jupyter Notebook

- An interactive web application for creating and sharing computational documents.

jupyter Untitled Last Checkpoint: 2 minutes ago (autosaved) Python 3 (ipykernel) Logout

File Edit View Insert Cell Kernel Widgets Help Trusted


```
In [1]: import pandas as pd
        from sklearn.datasets import load_wine

        wine_data = load_wine()

        wine_df = pd.DataFrame(wine_data.data, columns=wine_data.feature_names)
        wine_df["target"] = wine_data.target

        wine_df.head()
```

iris, house prices, diabetes, digits...



```
Out[1]:
```

alkalinity_of_ash	magnesium	total_phenols	flavanoids	nonflavanoid_phenols	proanthocyanins	color_intensity	hue	od280/od315_of_diluted_wines	proline	target
15.6	127.0	2.80	3.06	0.28	2.29	5.64	1.04	3.92	1065.0	0
11.2	100.0	2.65	2.76	0.26	1.28	4.38	1.05	3.40	1050.0	0
18.6	101.0	2.80	3.24	0.30	2.81	5.68	1.03	3.17	1185.0	0
16.8	113.0	3.85	3.49	0.24	2.18	7.80	0.86	3.45	1480.0	0
21.0	118.0	2.80	2.69	0.39	1.82	4.32	1.04	2.93	735.0	0

In [ ]:



# Scikit-Learn Example Continued...

```
from sklearn.preprocessing import StandardScaler
x = wine_df[wine_data.feature_names].copy()
y = wine_df["target"].copy()
scaler = StandardScaler()
scaler.fit(X)
X_scaled = scaler.transform(X.values)           //MinMaxScaler : (0,1)
print(X_scaled[0])                             //Other things possible: Missing val., Redundant val.

from sklearn.model_selection import train_test_split
X_train_scaled, X_test_scaled, y_train, y_test = train_test_split(X_scaled,
y, train_size=.7, random_state=25)

from sklearn.linear_model import LogisticRegression
logistic_regression = LogisticRegression()
logistic_regression.fit(X_train_scaled, y_train)
log_reg_preds = logistic_regression.predict(X_test_scaled)
```

Pre-processing

Building the model

# Classification Reports

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```
from sklearn.metrics import classification_report
```

```
# Store model predictions in a dictionary which makes it's  
easier to iterate through the model and print the results.
```

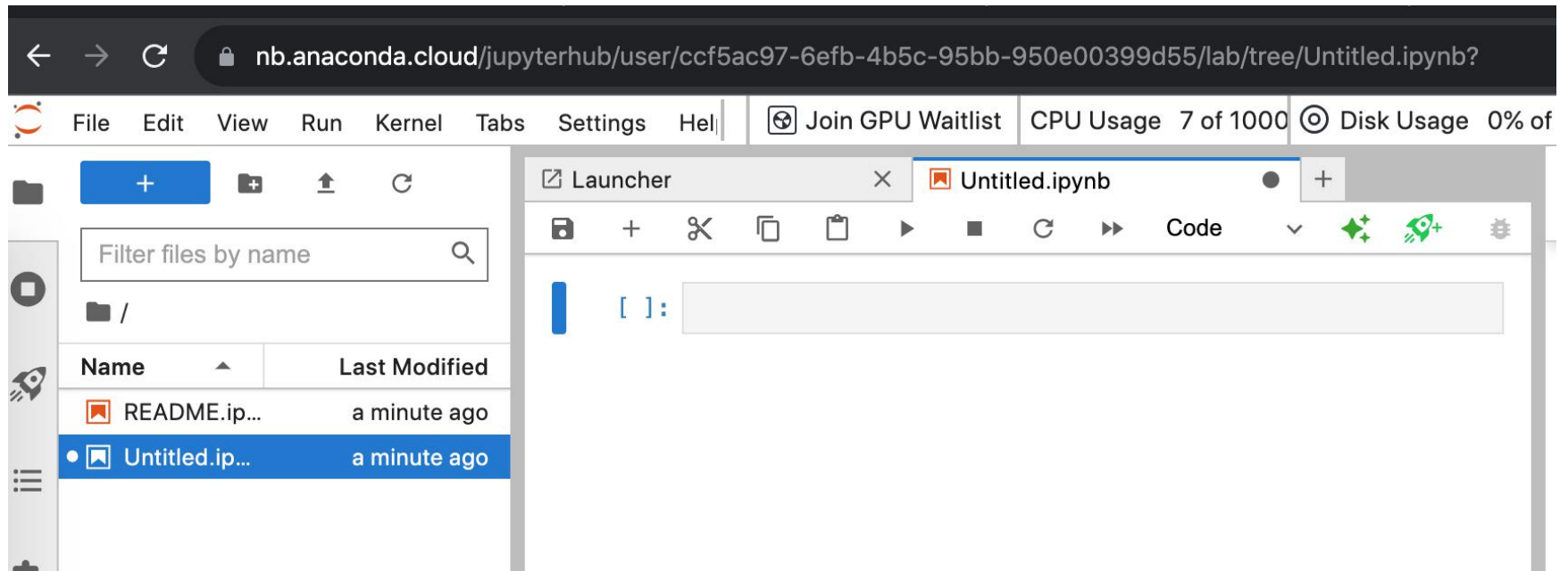
```
Logistic Regression Results:
```

	precision	recall	f1-score	support
0	1.00	1.00	1.00	17
1	1.00	0.92	0.96	25
2	0.86	1.00	0.92	12
accuracy			0.96	54
macro avg	0.95	0.97	0.96	54
weighted avg	0.97	0.96	0.96	54



# Anaconda Cloud Option

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You can install in both the standalone and cloud options, many other packages/ libraries like:



# An alternative to Anaconda

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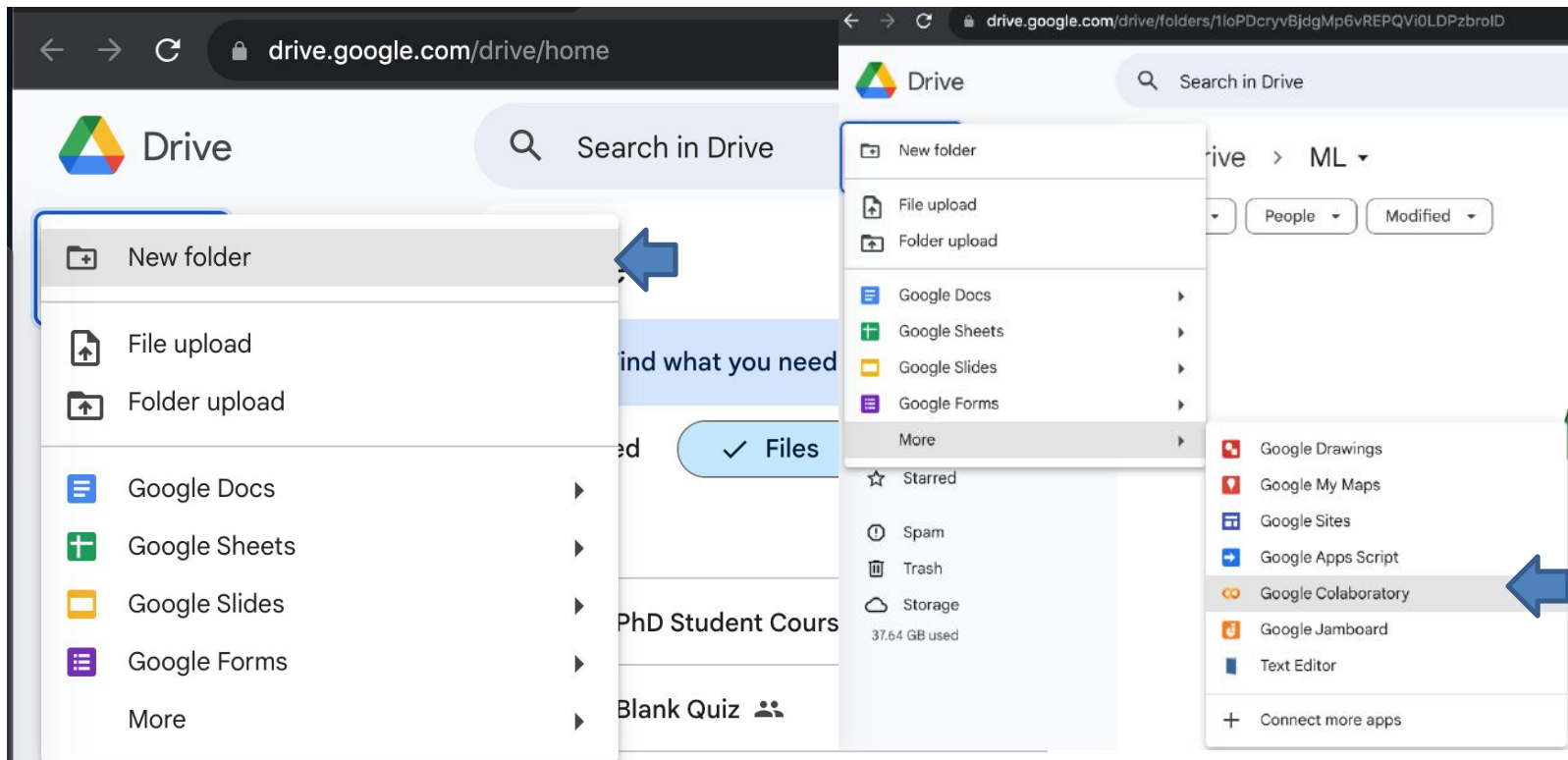


Google Colaboratory

- Sharing is allowed in which one?
  - More powerful hardware (TPU/ GPU etc. are available in which one?
-

# Google Colab Continued...

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# Continued...

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The screenshot displays a Google Colab notebook interface. The browser address bar shows 'colab.research'. The notebook title is 'Lregression.ipynk'. The menu bar includes 'File', 'Edit', 'View', and 'Insert'. Below the menu, there are buttons for '+ Code' and '+ Text'. A code cell is visible with a play button icon, a green checkmark, and a '0s' execution time. The code is `print("Hello Wo` and the output is 'Hello World'. On the right side, the 'Resources' panel is open, showing a message: 'You are not subscribed. Learn more. You currently have zero compute units available. Resources offered free of charge are not guaranteed. Purchase more units here. Manage sessions'. Below this is a button to 'Upgrade to Colab Pro'. The resources section also displays 'Python 3 Google Compute Engine backend' and 'Showing resources from 9:04 PM to 9:05 PM'. Two resource usage graphs are shown: 'System RAM' at 0.8 / 12.7 GB and 'Disk' at 26.3 / 107.7 GB.

colab.research

Comment Share

RAM  
Disk

Lregression.ipynk

File Edit View Insert

+ Code + Text

0s `print("Hello Wo`

Hello World

Resources ×

You are not subscribed. [Learn more](#).  
You currently have zero compute units available. Resources offered free of charge are not guaranteed. Purchase more units [here](#).  
[Manage sessions](#)

Want more memory and disk space? [Upgrade to Colab Pro](#) ×

Python 3 Google Compute Engine backend  
Showing resources from 9:04 PM to 9:05 PM

System RAM  
0.8 / 12.7 GB

Disk  
26.3 / 107.7 GB

# Continued...

This is the first statement in Co

```
import numpy as np
import matplotlib.pyplot as plt
import sklearn

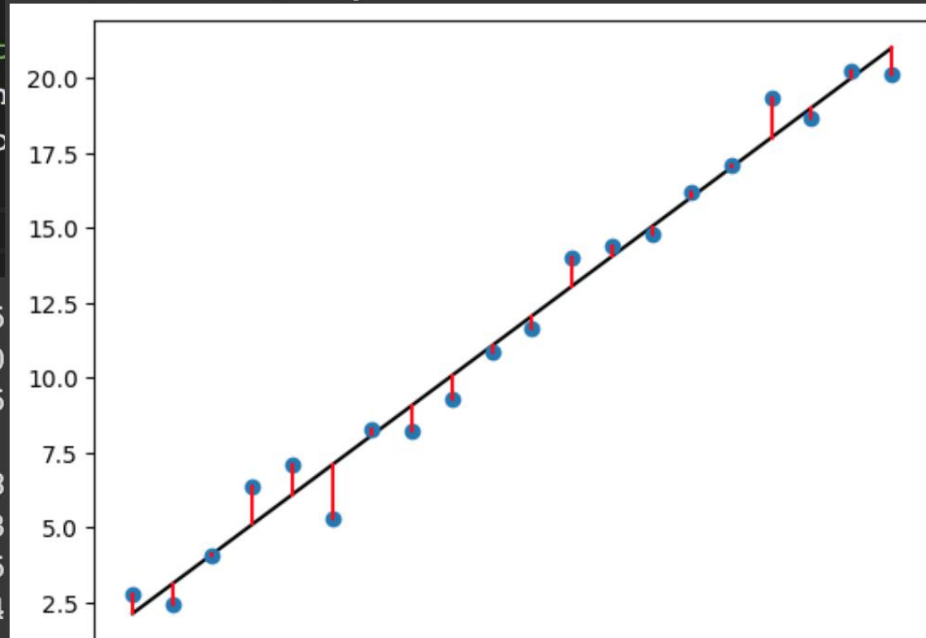
np.random.seed(0)
n=20 # Number of data points
x=np.linspace(0, 10, n)
y=x*2 + 1 + 1*np.random.randn(n)
print(x)
print(y)
```

```
[ 0.          0.52631579
 3.15789474  3.68421053
 6.31578947  6.84210526
 9.47368421 10.          ]
[ 2.76405235  2.45278879
 8.26587789  8.21706384
14.39261667 14.80588554
20.26043612 20.14590426]
```

```
from sklearn.linear_model import LinearRegression

model=LinearRegression(fit_intercept=True)
model.fit(x[:,np.newaxis], y)
xfit=np.linspace(0,10,100)
yfit=model.predict(xfit[:, np.newaxis])
plt.plot(xfit,yfit, color="black")
plt.plot(x,y, 'o')
# The following will draw as many line segments as there are columns in matrices x and y
plt.plot(np.vstack([x,x]), np.vstack([y, model.predict(x[:, np.newaxis])]), color="red");
```

```
[ 0.          0.52631579  1.05263158  1.57894737  2.10526316  2.63157895
 3.15789474  3.68421053  4.21052632  4.73684211  5.26315789  5.78947368
 6.31578947  6.84210526  7.36842105  7.89473684  8.42105263  8.94736842
 9.47368421 10.          ]
[ 2.76405235  2.45278879  4.08400114  6.39878794  7.07808431  5.28588001
 8.26587789  8.21706384  9.31783378 10.88428271 11.67035936 14.03322088
14.39261667 14.80588554 16.18070534 17.12314801 19.33618434 18.68957858
20.26043612 20.14590426]
```

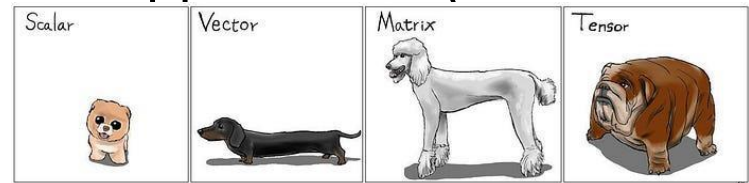




# TensorFlow



- Supports distributed ML
- Large-scale ML models in real-world applications (Production environment)
- What is a Tensor?
  - A multi-dimensional array on which mathematical operations can be performed. (Ex: Addition of two tensors)



- GPU acceleration for Tensors

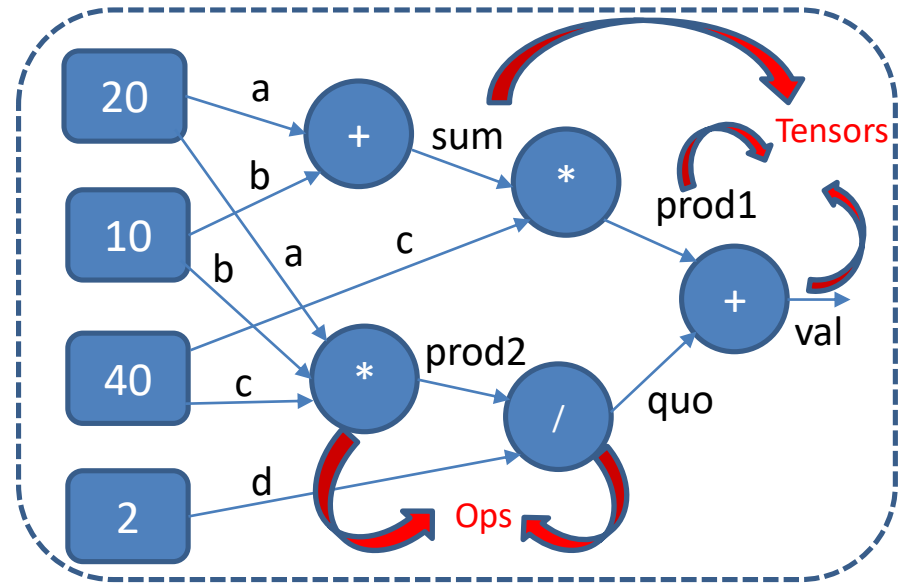




# TensorFlow: Computational Graphs

```
▶ import tensorflow as tf
a = 20
b = 10
c = 4
d = 2
sum = a + b
prod1 = sum * c
prod2 = a * b * c
quo = prod2 / d
val = prod1 + quo
print(val)
```

520.0



```
▶ # Load the TensorBoard notebook extension.
%load_ext tensorboard
import tensorboard
```

For you to explore...

# TensorFlow with Keras

```
import tensorflow as tf
print("TensorFlow version:", tf.__version__)
mnist = tf.keras.datasets.mnist
(x_train, y_train), (x_test, y_test) = mnist.load_data()
x_train, x_test = x_train / 255.0, x_test / 255.0
model = tf.keras.models.Sequential([
    tf.keras.layers.Flatten(input_shape=(28, 28)),
    tf.keras.layers.Dense(128, activation='relu'),
    tf.keras.layers.Dropout(0.2),
    tf.keras.layers.Dense(10)
])
predictions = model(x_train[:1]).numpy()
predictions
tf.nn.softmax(predictions).numpy()
loss_fn = tf.keras.losses.SparseCategoricalCrossentropy(from_logits=True)
loss_fn(y_train[:1], predictions).numpy()
model.compile(optimizer='adam', loss=loss_fn, metrics=['accuracy'])

model.fit(x_train, y_train, epochs=5)
model.evaluate(x_test, y_test, verbose=2)
```

```
TensorFlow version: 2.15.0
Epoch 1/5
1875/1875 [=====] - 7s 3ms/step - loss: 0.3028 - accuracy: 0.9119
Epoch 2/5
1875/1875 [=====] - 8s 4ms/step - loss: 0.1480 - accuracy: 0.9566
Epoch 3/5
1875/1875 [=====] - 6s 3ms/step - loss: 0.1115 - accuracy: 0.9665
Epoch 4/5
1875/1875 [=====] - 7s 4ms/step - loss: 0.0908 - accuracy: 0.9724
Epoch 5/5
1875/1875 [=====] - 7s 3ms/step - loss: 0.0776 - accuracy: 0.9768
313/313 - 1s - loss: 0.0774 - accuracy: 0.9756 - 553ms/epoch - 2ms/step
[0.07737699896097183, 0.975600004196167]
```



```
epoch 0, loss 67.04987335205078
epoch 1, loss 30.550050735473633
epoch 2, loss 14.291292190551758
epoch 3, loss 7.043418884277344
epoch 4, loss 3.807079315185547
epoch 5, loss 2.356700897216797
epoch 6, loss 1.701522707939148
epoch 7, loss 1.4004793167114258
epoch 8, loss 1.2572226524353027
epoch 9, loss 1.1843408346176147
epoch 10, loss 1.1429182291030884
```

...

```
epoch 489, loss 0.0010938026243820786
epoch 490, loss 0.0010780788725242019
epoch 491, loss 0.001062584575265646
epoch 492, loss 0.0010473171714693308
epoch 493, loss 0.0010322668822482228
epoch 494, loss 0.0010174255585297942
epoch 495, loss 0.001002818695269525
epoch 496, loss 0.0009883942548185587
epoch 497, loss 0.0009741996182128787
epoch 498, loss 0.0009601832716725767
epoch 499, loss 0.0009463919559493661
predict (after training) 4 7.964635848999023
```

```
import torch
from torch.autograd import Variable

x_data = Variable(torch.Tensor([[1.0], [2.0], [3.0]]))
y_data = Variable(torch.Tensor([[2.0], [4.0], [6.0]]))

class LinearRegressionModel(torch.nn.Module):

    def __init__(self):
        super(LinearRegressionModel, self).__init__()
        self.linear = torch.nn.Linear(1, 1) # One in and one out

    def forward(self, x):
        y_pred = self.linear(x)
        return y_pred

our_model = LinearRegressionModel()

criterion = torch.nn.MSELoss(size_average = False)
optimizer = torch.optim.SGD(our_model.parameters(), lr = 0.01)

for epoch in range(500):
    # Forward pass: Compute predicted y by passing x to the model
    pred_y = our_model(x_data)

    # Compute and print loss
    loss = criterion(pred_y, y_data)

    # Zero gradients, perform a backward pass, and update the weights.
    optimizer.zero_grad()
    loss.backward()
    optimizer.step()
    print('epoch {}, loss {}'.format(epoch, loss.item()))

new_var = Variable(torch.Tensor([[4.0]]))
pred_y = our_model(new_var)
print("predict (after training)", 4, our_model(new_var).item())
```

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Thank you!

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