**Intro**: Today we’re gonna present the paper, A Comprehensive Survey on Transfer Learning.

**Photo:** This is us, Eduardo, me, Rohit, and Stuart

**Outline:**

For the first section, we are going to give you an overview of the paper but not going into too much details into it, since we’re short on time. Then, in the next section, we’re going to focus on 1 of the methods and dig deeper into it.

Lastly, we are going to show you a quick demo of how to implement this method.

Just a **quick overview on Transfer Learning:**

Transfer learning is a generalization of experience, so there needs to be a connection between the source and the target.

* If we have a homogenous task, then source and the target domain have the same feature space. They’ll just differ in marginal distributions.
* If we have heterogenous tasks, then the source and domain will have different feature, and we need to put more work to adapt the feature space and distribution.

This paper will particularly focus on methods for homogenous tasks. Anything in brown are not covered in the paper.

**Negative Transfer:** Another important point is that transfer learning doesn’t ALWAYS work. We may not have any information that can be shared between the source and the target. In other cases, learning 1 tasks may actually have a negative impact to learn a second task. This is something we would want to avoid.

This is how the paper **categorize the problem**. To do transfer learning, we can look at how the data were labeled, or we can look at the feature space. The right branch (i.e. for feature & label information -> homogenous tasks), is where we are going to focus on.

The paper also put some **categorization on the solution**. We can solve it from 4 different perspective.

* First, we can look at the instance itself and see if we can put some weights on it to make the information transferrable
* Secondly, we can look at the feature space and see what transformation is needed to transfer the knowledge.
* Third, we can look at the parameter directly, and just transfer the parameters of the source to the target.
* There is also relational based solution, but the paper does not cover this.

Now to solve the problem for transfer learning, we can do it 2 ways, from the **data** **perspective**, or from the model perspective. From the data perspective, we can have 2 different **strategies**:

* Firstly, we can look at the data instances, i.e. use some techniques to weigh the instances of the source domain to match what we have in the target domains.
* Secondly, we are going to look at the feature space, i.e. what kind of transformation do we need to implement to the source or target domains to make sure they match. 3 main ways to do this is by doing some feature augmentation, feature reduction, or feature alignment

Now to solve the TL problem from the data perspective, there are the main **objective** we are going to focus on. We can focus on how to do the space adaptation (by looking at either the label or the feature space), how to adapt the distribution (which can be done with various different metric as well), and how to preserve or adjust the data property.

Now going on to look at TL from the **model** **perspective**, similarly, we can categorize both the strategy and the objective. There are 4 main strategies we can take, by controlling the model, controlling the parameter, combining the models with ensemble methods, or using some deep learning techniques. Looking at the objective, we can have focus on these 3 main goals, which is about how to make the prediction, how to adapt the domains of the source & target, and how to generate pseudo-label.

We all know that transfer learning is very powerful and can be applied to many different industries. These are 6 main applications that are discussed in the paper (explain if we have time, or skip the details otherwise).