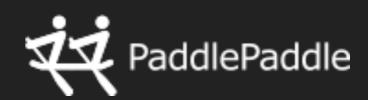


PARALLEL AND DISTRIBUTED DEEP LEARNING

PADDLEPADDLE

- Introduction
- PaddlePaddle Fluid
- Elastic Distributed Training
- Multi-GPU
- Sequence Model and LoDTensor
- Official Resources

INTRODUCTION



Official Website: http://paddlepaddle.org/

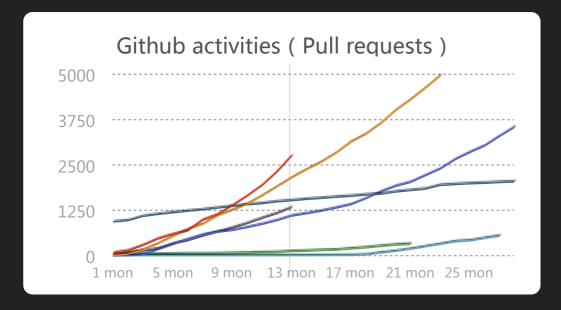


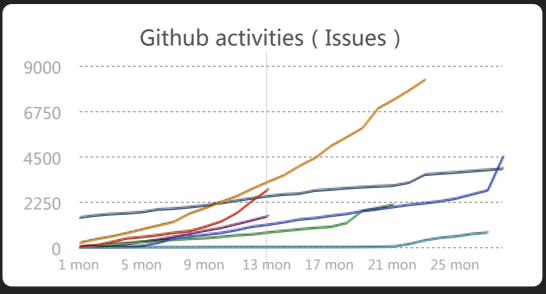
Github: https://github.com/PaddlePaddle/Paddle

- Deep Learning Platform for both Enterprise & Research
- Easy-to-use, Flexibility, Efficiency and Scalability
- Official Release: pypi and Docker image

A BIT HISTORY

- ▶ 2013 Start PaddlePaddle Project
- 2014~2016 Wins Baidu Highest Award
- ▶ 2016~2017 Open Source and rapid growth





- PaddlePaddle
- TensorFlow
- Caffe
- MXNet
- PyTorch
- Caffe2
- CNTK

WHY WE START THE PADDLEPADDLE PROJECT?

- Make use of billion data
- People do not have such open source platforms in 2013
- Toolkits on deep learning were about image recognition in 2013
- Requirement: Products around Our Search Engine
- Text based Problem (Natural Language Understanding)

PADDLEPADDLE IN BAIDU

supports many online products

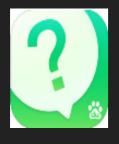


































CONTEXT DIAGRAM FOR PADDLEPADDLE Cloud RESEARCHERS **Supports DEVELOPERS** Community **COMPANIES** du = Github Kubernetes **Maintains Pull Request Contributes** Contributes Continus Integration Pull Images Python PaddlePaddle Docker Travis CI Go Executes on Visualizes Refactor From the Inside of Container CPU **GPU**

Jupyter

Platform

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PADDLEPADDLE FLUID

```
# block 0
x = sequence([10, 20, 30])
m = var(0)
W = var(0.314, param=true)
U = var(0.375, param=true)
rnn = pd.rnn()
with rnn.step():
                      # block 1
  x_ = rnn.step_input(x)
 h = rnn.memory(init = m)
  hh = rnn.previous_memory(h)
  a = layer.fc(W, x_{-})
  b = layer.fc(U, hh)
  s = pd.add(a, b)
  act = pd.sigmoid(s)
  rnn.update_memory(h, act)
  rnn.output(a, b)
01, 02 = rnn()
```

```
// block 0
int* x = \{10, 20, 30\};
int* m = {0};
int* W = \{0.314\};
int* U = {0.375};
int len = sizeof(x) / sizeof(x[0])
int mem[len + 1];
int p1[len + 1];
int o2[len + 1];
for (int i = 1; i \le len; ++i) { // block 1
  int x = x[i-1]:
  if (i == 1) mem[0] = m;
  int* hh = &(mem[i-1]);
  int a = W * x;
  int b = Y * *hh:
  int s = fc_out + hidden_out;
  int act = sigmoid(sum);
  mem[i] = act;
  o1[i] = act; o2[i] = hidden_out;
```

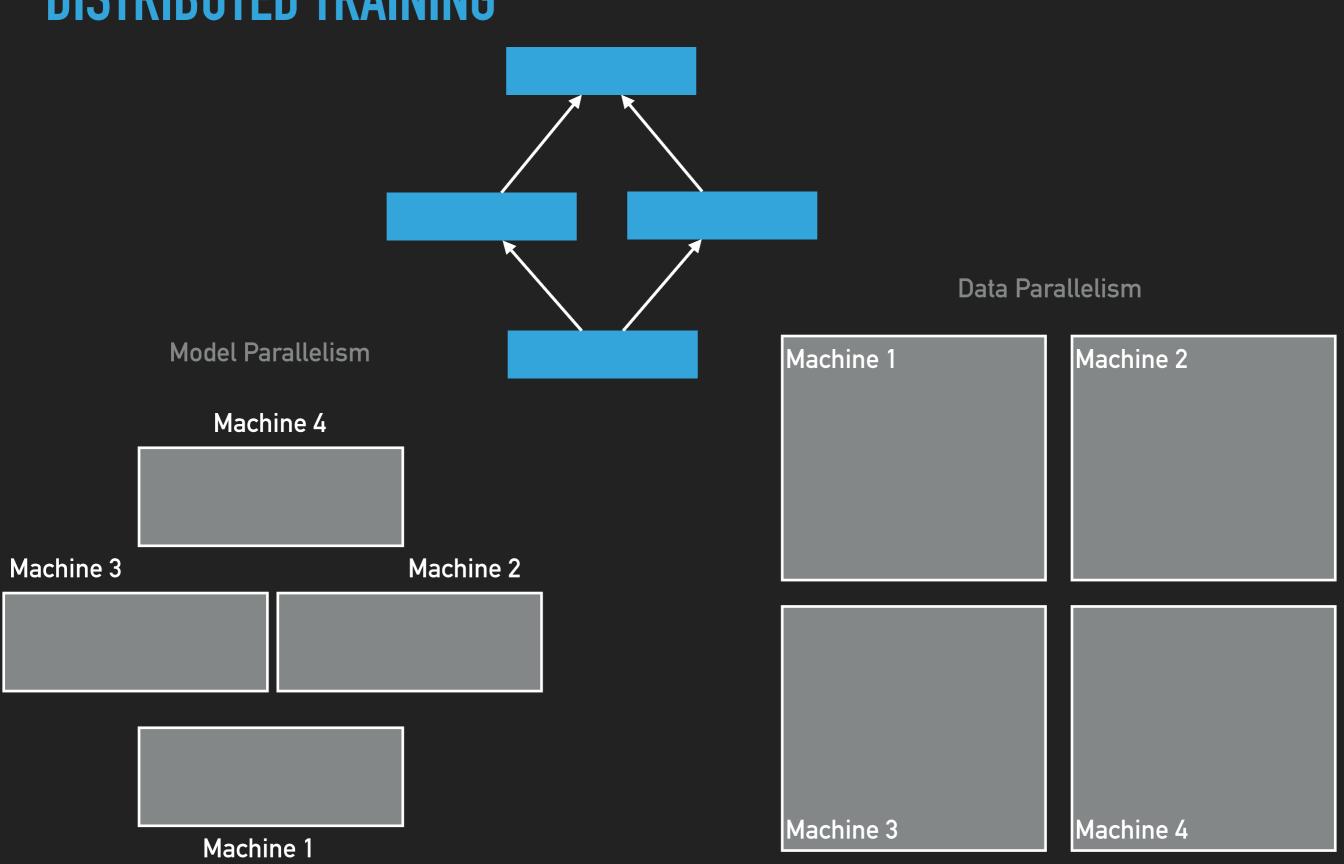


PADDLEPADDLE FLUID

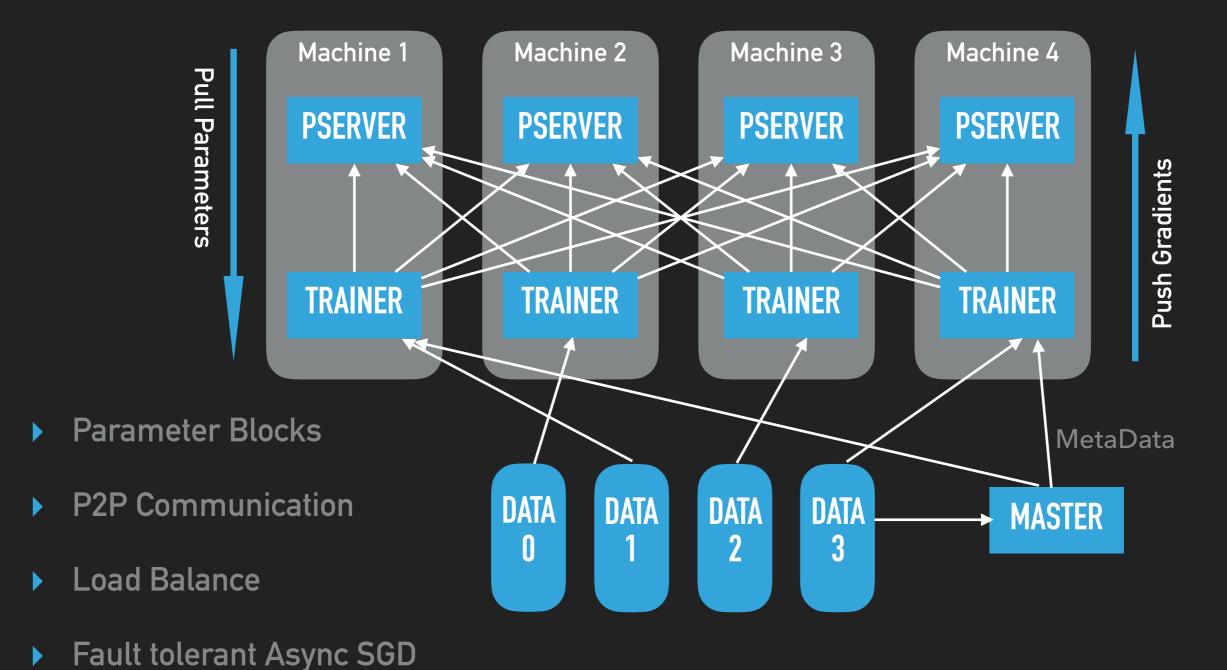
- High level programing API
 - Write like a High-level Programing Language
 - Compatible with legacy API
 - Implemented using operators
- Current Status:
 - Development Complete (single machine)
 - IfElse/While Operators
 - Better support for GAN/RL

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DISTRIBUTED TRAINING



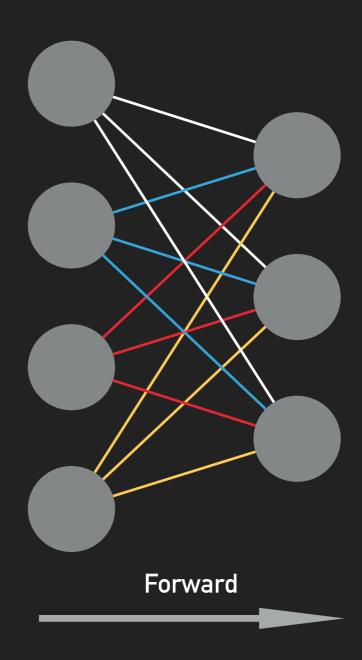
FAULT TOLERANT DISTRIBUTED TRAINING



Checkpointing

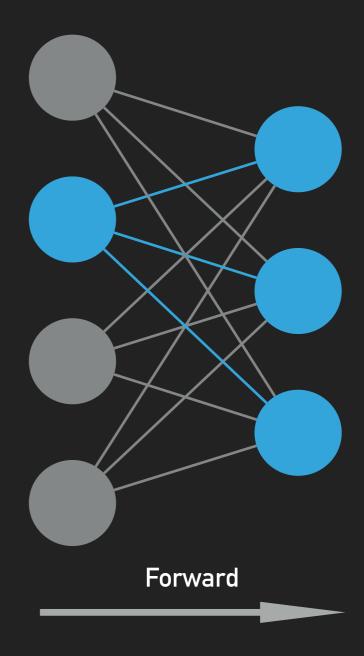
SPLIT PARAMETER BLOCKS

- Parameters: links between two layers
- Parameters will be divided equally
- Division Operation:
 - 4 Parameter Servers: {White, Blue, Red, Yellow}
 - Yellow 3 Parameter Servers: {White, Blue, (Red, Yellow)}
- Sparse Training
- Customizable block hashing method (On Roadmap)



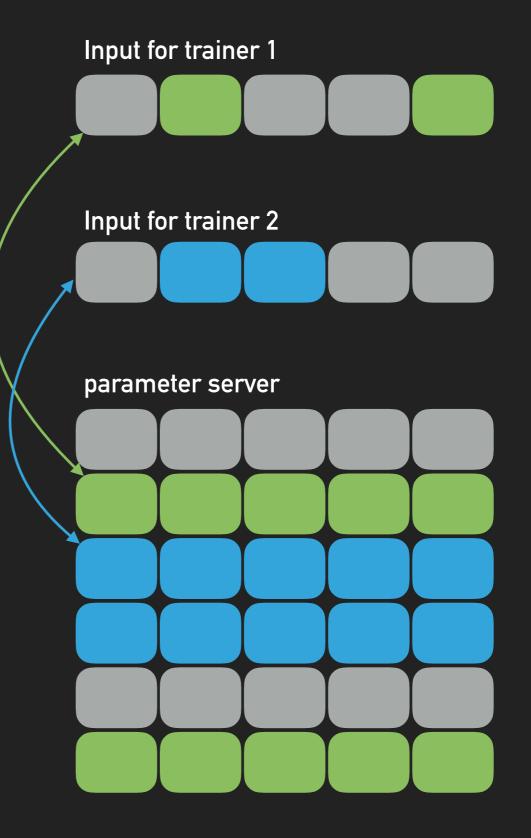
SPARSE TRAINING

- Sparse Training: Input is sparse
- Gray neuron and links: have no effect
 - output is 0, gradient is 0
 - no update (simple SGD)
- Blue neuron and links really matters
 - pull new parameter from PServer
 - calculate gradients, push to PServer



DISTRIBUTED SPARSE TRAINING

- Prefetch Operations
 - First, always beforehand scan training data
 - Label the corresponding parameters
 - Pull the latest parameter from PServer
- Forward/Backward
 - calculate gradients, push them to PServer



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DISTRIBUTED VS SINGLE MACHINE

- Distributed training isn't free
- Overhead
 - Synchronization
 - Network transfer data
 - Setup time (preparing and loading training data)
 - hyperparameter tuning
- Training on single machine until time becomes prohibitive

OVER-FITTING?
MULTI-GPU OR
DISTRIBUTED

DISTRIBUTED

Network Size

SINGLE MACHINE

UNDER-FITTING?
MULTI-GPU OR
DISTRIBUTED

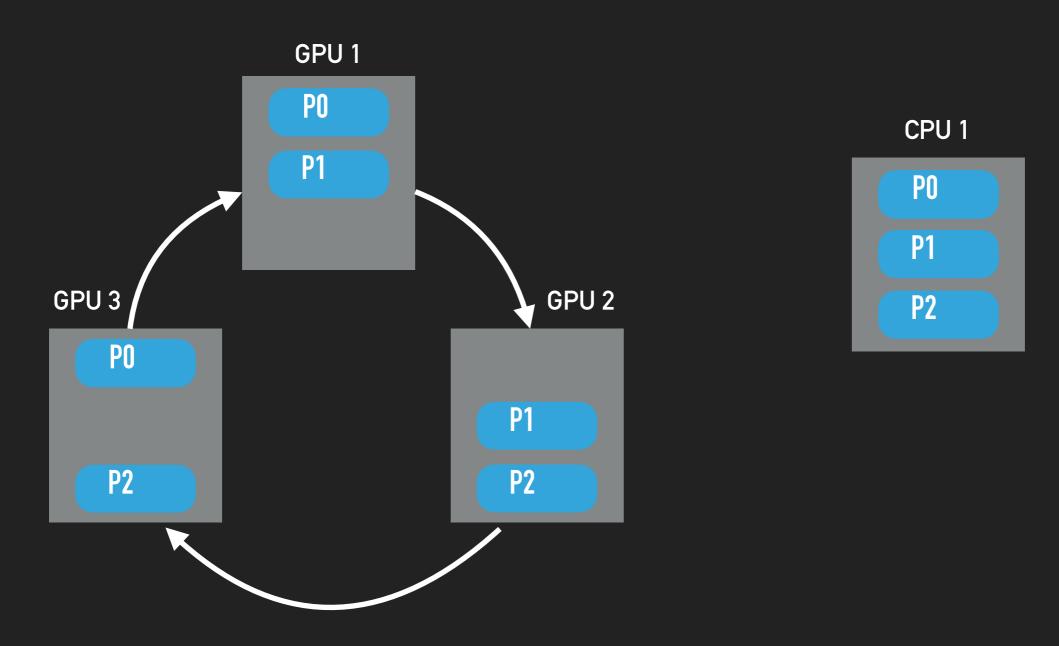
Data Size

DISTRIBUTED VS SINGLE MACHINE

- Another Perspective:
 - the ratio of network transfers to computation
- Distributed Training is more efficient when the ratio is low
 - small and shallow networks are not good candidates
 - increase batch size and learning rate
- Thus, in some cases, multi-GPU system is considered before

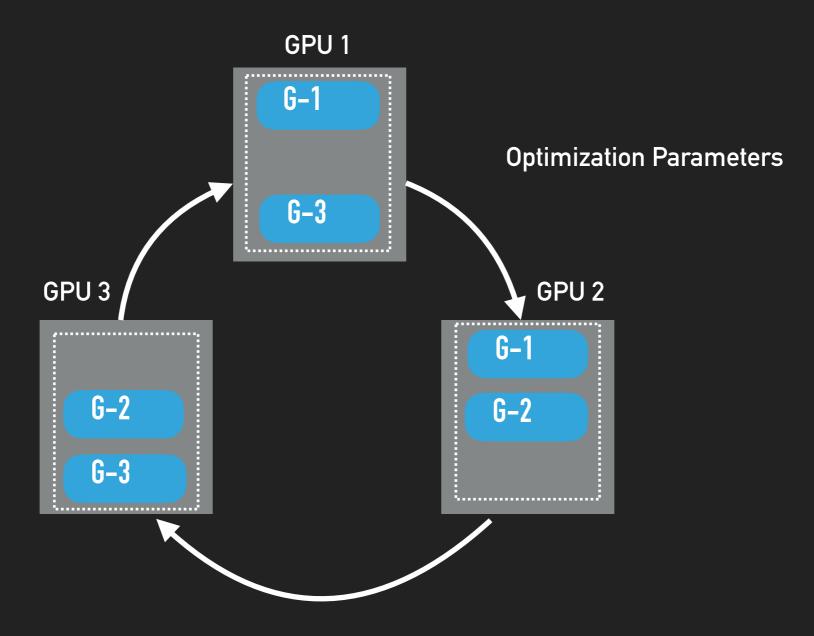
MULTI-GPU COMMUNICATION

- Ring-based network communication
- Hand out Parameters: each parameter has a master card



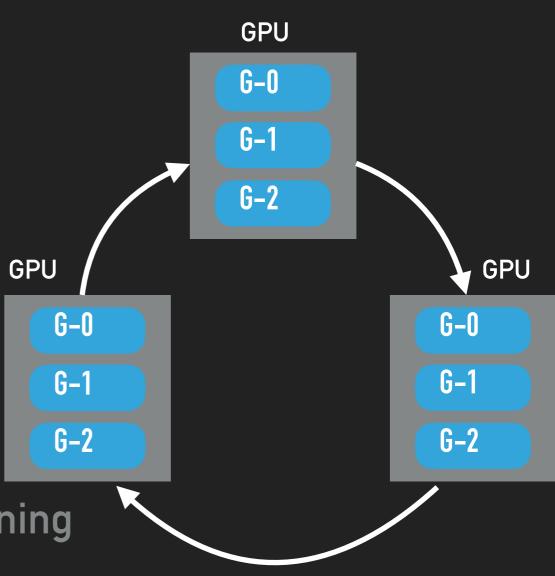
MULTI-GPU COMMUNICATION IN PADDLEPADDLE

Ring-based network communication



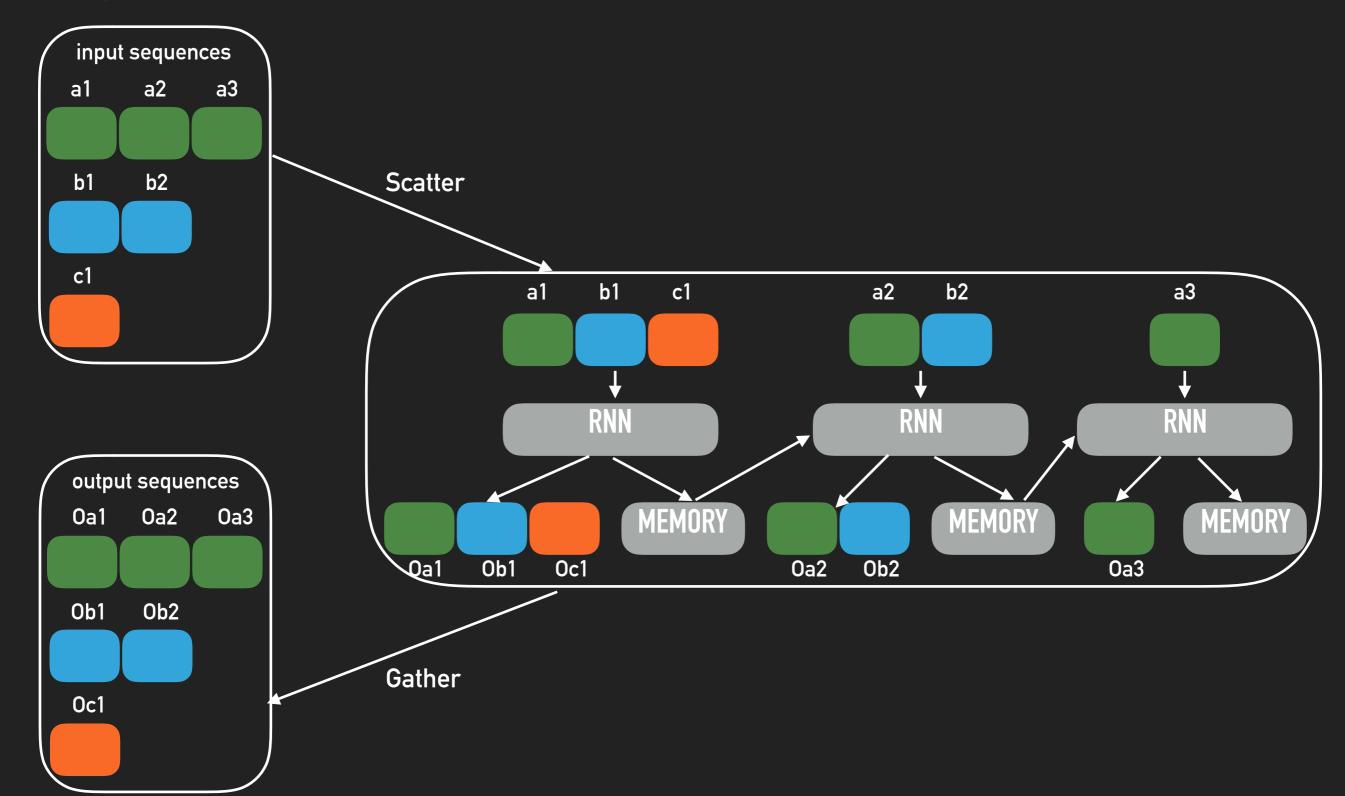
MULTI-GPU COMMUNICATION IN PADDLEPADDLE

- Ring-based network communication
- Advantages:
 - SGD method is simple
 - network communication utilization
 - coarse-grained synchronization
- Disadvantages:
 - no Async SGD
 - network overhead when sparse training

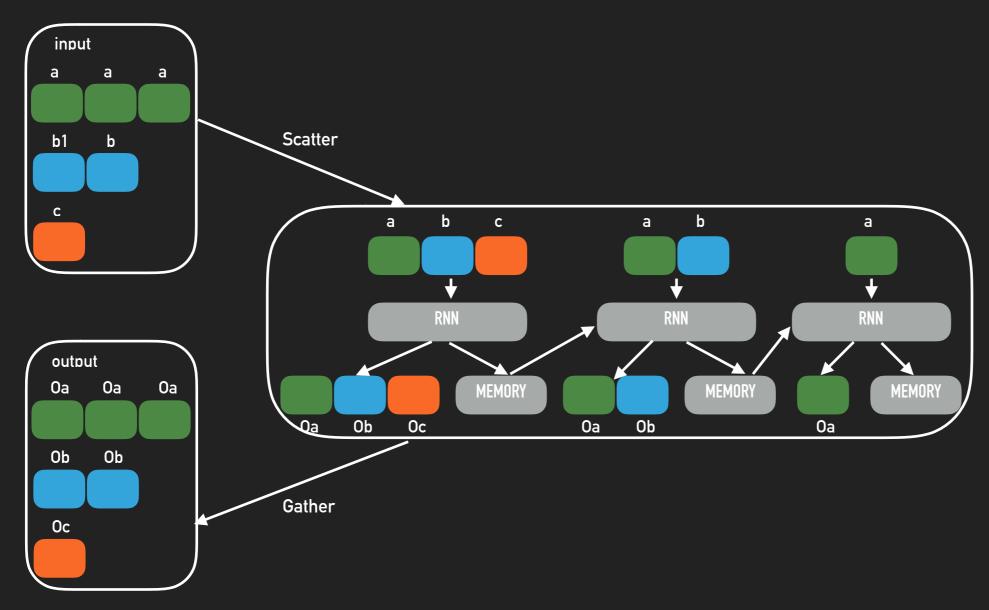


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SEQUENCE MODEL IN PADDLE PADDLE



SEQUENCE MODEL IN PADDLEPADDLE



- Support arbitrary complicated RNN
- No Padding
- Efficiently batch processing

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OFFICIAL SITE AND DOCUMENTS

http://www.paddlepaddle.org



PADDLEPADDLE BOOK

http://www.paddlepaddle.org/docs/develop/book/01.fit_a_line/

₹ PaddlePaddle

Deep Learning 101

Linear Regression

Linear Regression

Recognize Digits

Image Classification

Word2Vec

Personalized Recommendation

Sentiment Analysis

Semantic Role Labeling

Machine Translation

Let us begin the tutorial with a classical problem called Linear Regression [1]. In this chapter, we will train a model from a realistic dataset to predict home prices. Some important concepts in Machine Learning will be covered through this example.

The source code for this tutorial lives on book/fit_a_line. For instructions on getting started with PaddlePaddle, see PaddlePaddle installation guide.

Problem Setup

Suppose we have a dataset of n real estate properties. Each real estate property will be referred to as homes in this

Linear Regression

Documentation Book Models Mobile develop -

Problem Setup

Results Demonstration

English Github

中文 Github

Model Overview

Dataset

Training

Summary

References

₹ PaddlePaddle

深度学习入门 线性

新手入门

识别数字

图像分类

词向量

个性化推荐

情感分析

语义角色标注

机器翻译

线性回归

让我们从经典的线性回归(Linear Regression [1])模型开始这份教程。在这一章里,你将使用真实的数据集建立起一个房价预测模型,并且了解到机器学习中的若干重要概念。

本教程源代码目录在book/fit_a_line, 初次使用请参考PaddlePaddle安装教程,更多内容请参考本教程的视频课堂。

背景介绍

给定一个大小为n的数据集 $\{y_i,x_{i1},\ldots,x_{id}\}_{i=1}^n$,其中 x_{i1},\ldots,x_{id} 是第i个样本d个属性上的取值, y_i 是该样本待预测的目

线性回归

develop -

背景介绍 效果展示

模型概览

数据集

训练

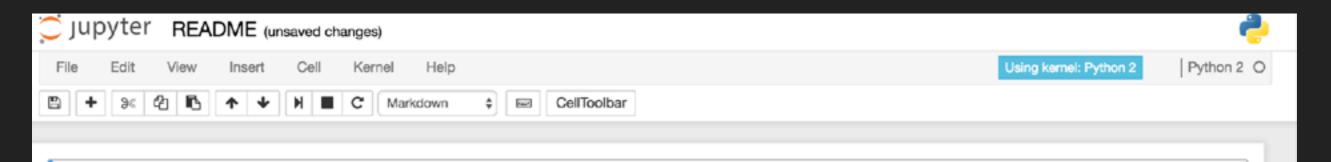
总结

参考文献

DOCKER BASED JUPYTER INTERACTIVE NOTEBOOK

- Documents that contain live code, equations, visualizations and explanatory text in a single browser.
- 1. Pull and Run the book image:
 - DockerHub.com:
 - docker run -d -p 8888:8888 paddlepaddle/book
 - docker.paddlepaddle.org: (user in China)
 - docker run -d -p 8888:8888 docker.paddlepaddle.org/book
- 2. Local browser:
 - http://localhost:8888/

DOCKER BASED JUPYTER INTERACTIVE NOTEBOOK



个性化推荐

本教程源代码目录在book/recommender system, 初次使用请参考PaddlePaddle安装教程。

背景介绍

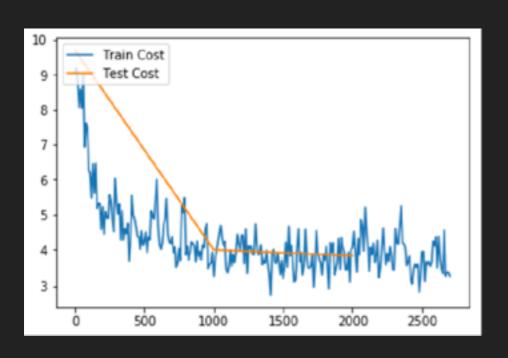
在网络技术不断发展和电子商务规模不断扩大的背景下,商品数量和种类快速增长,用户需要花费大量时间才能找到自己想买的商品,这就是信息超载问题。为了解决这个难题、推荐系统(Recommender System)应运而生。

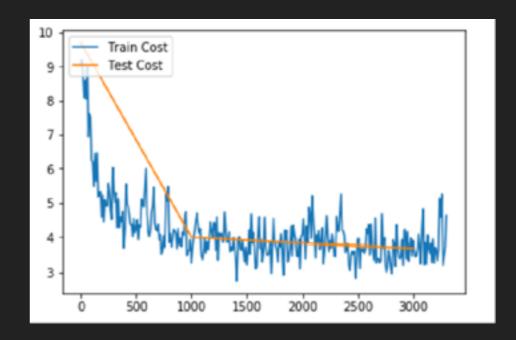
个性化推荐系统是信息过滤系统(Information Filtering System)的子集,它可以用在很多领域,如电影、音乐、电商和 Feed 流推荐等。推荐系统通过分析、挖掘用户行为,发现用户的个性化需求与兴趣特点,将用户可能感兴趣的信息或商品推荐给用户。与搜索引擎不同,推荐系统不需要用户准确地描述出自己的需求,而是根据分析历史行为建模,主动提供满足用户兴趣和需求的信息。

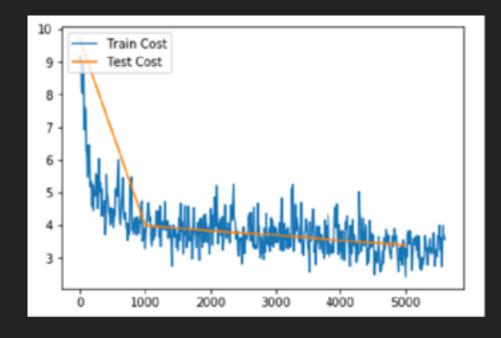
传统的推荐系统方法主要有:

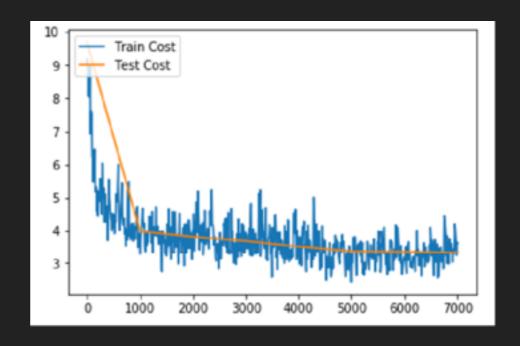
- 协同过滤推荐(Collaborative Filtering Recommendation):该方法收集分析用户历史行为、活动、偏好,计算一个用户与其他用户的相似度,利用目标用户的相似用户对商品评价的加权评价值,来预测目标用户对特定商品的喜好程度。优点是可以给用户推荐未浏览过的新产品;缺点是对于没有任何行为的新用户存在冷启动的问题,同时也存在用户与商品之间的交互数据不够多造成的稀疏问题,会导致模型难以找到相近用户。
- 基于内容过滤推荐[1](Content-based Filtering Recommendation):该方法利用商品的内容描述,抽象出有意义的特征,通过计算用户的兴趣和商品描述之间的相似度,来给用户做推荐。优点是简单直接,不需要依据其他用户对商品的评价,而是通过商品属性进行商品相似度度量,从而推荐给用户所感兴趣商品的相似商品;缺点是对于没有任何行为的新用户同样存在冷启动的问题。
- 组合推荐[2] (Hybrid Recommendation): 运用不同的输入和技术共同进行推荐,以弥补各自推荐技术的缺点。

DOCKER BASED JUPYTER INTERACTIVE NOTEBOOK



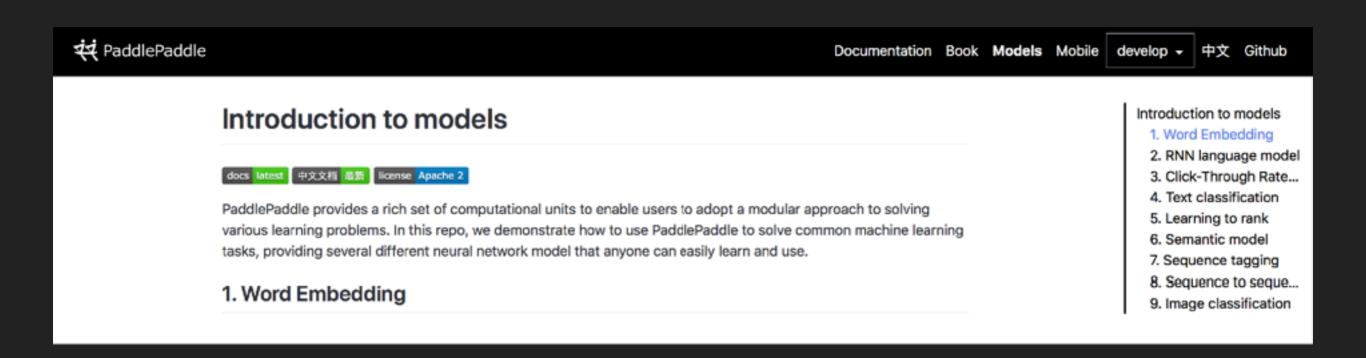






PRODUCTION LEVEL MODEL BANK

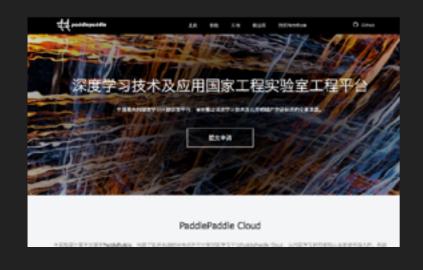
- http://www.paddlepaddle.org/docs/develop/models/ README.html
- Pre-Trained models

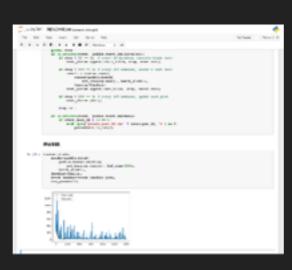


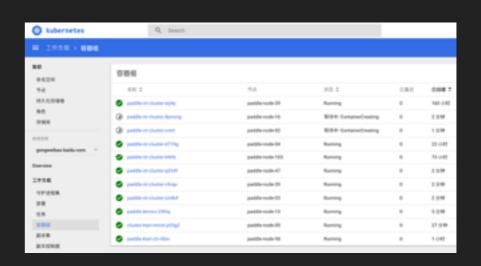
PADDLEPADDLE CLOUD

- https://github.com/PaddlePaddle/cloud
- http://cloud.dlnel.org

深度学习开发方式的变革:开发、实验、分布式任务一键提交







- Introduction
- PaddlePaddle Fluid
- Elastic Distributed Training
- Sequence Model and LoDTensor
- Official Resources



THANK YOU