

CS535 BIG DATA

PART 2. SCALABLE FRAMEWORKS FOR REAL-TIME BIG DATA ANALYTICS
1. SPEED LAYER: APACHE STORM

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FAQs

- Term project proposal due on Friday
- Your presentation will be next week
- **IMPORTANT:** Please send me your slides at least 2 hours before your presentation

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Today's topics

- SGD
- Speed Layer
- Apache Storm
 - Word count example
 - Parallelism

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Using Gradient Descent Algorithm for Linear Regression Model

Gradient descent algorithm	Linear Regression Model
Repeat until convergence { $\theta_0 - \alpha \frac{\partial}{\partial \theta_0} J(\theta_0, \theta_1)$ $\theta_1 - \alpha \frac{\partial}{\partial \theta_1} J(\theta_0, \theta_1)$ } (for j=0 and j=1)	$h_\theta(x) = \theta_0 + \theta_1 x_1$ $J(\theta) = \frac{1}{2m} \sum_{i=0}^m (h_\theta(x^{(i)}) - y^{(i)})^2$

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$$\frac{\partial}{\partial \theta_j} J(\theta_0, \theta_1) = \frac{\partial}{\partial \theta_j} \frac{1}{2m} \sum_{i=1}^m (h_\theta(x^{(i)}) - y^{(i)})^2$$

$$= \frac{\partial}{\partial \theta_j} \frac{1}{2m} \sum_{i=1}^m (\theta_0 + \theta_1 x^{(i)} - y^{(i)})^2$$

Case 1, θ_0 ($j = 0$) :

$$\frac{\partial}{\partial \theta_0} J(\theta_0, \theta_1) = \frac{\partial}{\partial \theta_0} \frac{1}{2m} \sum_{i=1}^m (h_\theta(x^{(i)}) - y^{(i)})^2 = \frac{1}{m} \sum_{i=1}^m (h_\theta(x^{(i)}) - y^{(i)})$$

Case 2, θ_1 ($j = 1$) :

$$\frac{\partial}{\partial \theta_1} J(\theta_0, \theta_1) = \frac{\partial}{\partial \theta_1} \frac{1}{2m} \sum_{i=1}^m (h_\theta(x^{(i)}) - y^{(i)})^2 = \frac{1}{m} \sum_{i=1}^m (h_\theta(x^{(i)}) - y^{(i)}) x^{(i)}$$

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Gradient descent for Linear Regression

Repeat until convergence {

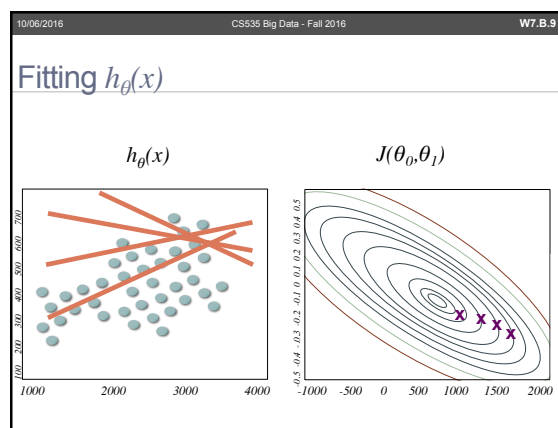
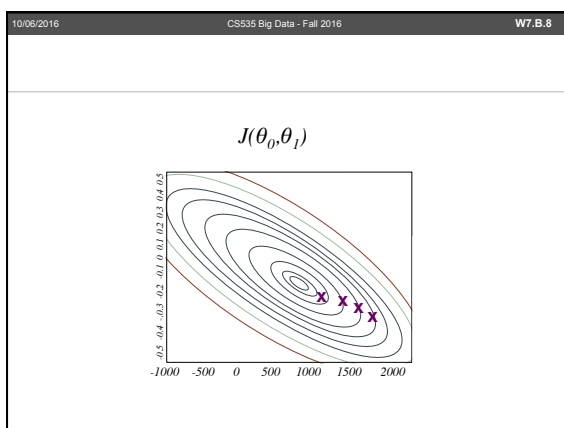
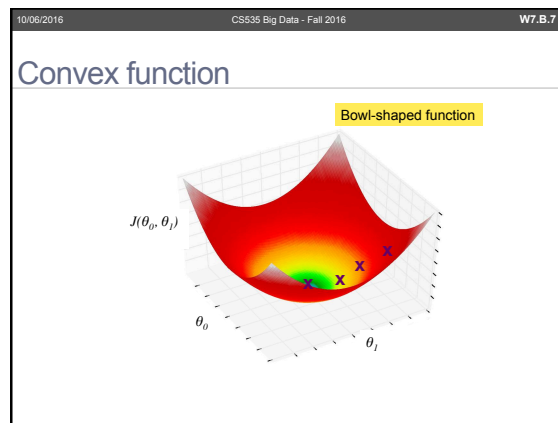
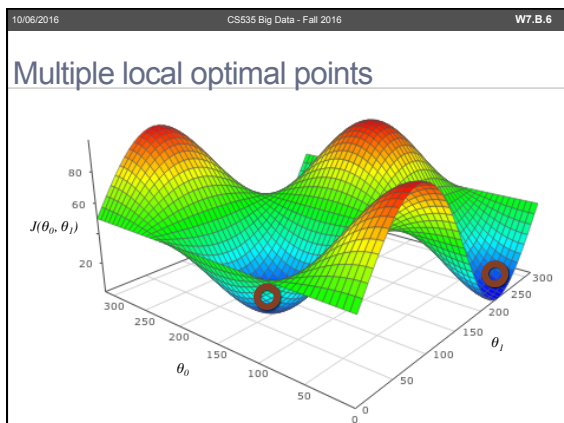
$$\theta_0 := \theta_0 - \alpha \frac{1}{m} \sum_{i=1}^m (h_\theta(x^{(i)}) - y^{(i)})$$

$$\theta_1 := \theta_1 - \alpha \frac{1}{m} \sum_{i=1}^m (h_\theta(x^{(i)}) - y^{(i)}) x^{(i)}$$

Update θ_0 and θ_1 simultaneously

(for j=0 and j=1)

}



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"Batch" Gradient Descent

- Batch
 - Each step of gradient descent uses all of the training example

$$\theta_j := \theta_j + \alpha \frac{1}{m} \sum_{i=1}^m (y^{(i)} - h_\theta(x^{(i)})) x_j^{(i)}$$

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Running with Spark in parallel

- For the sample size 1,000 ($m=1,000$)
- Batch gradient descent:

$$\theta_j := \theta_j + \alpha \frac{1}{1,000} \sum_{i=1}^{1000} (y^{(i)} - h_\theta(x^{(i)})) x_j^{(i)}$$
- Using 4 machines

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continued

- Step 1. 4 input splits
- $(x^{(1)}, y^{(1)}), \dots, ((x^{(250)}, y^{(250)}))$
- $(x^{(251)}, y^{(251)}), \dots, ((x^{(500)}, y^{(500)}))$
- $(x^{(501)}, y^{(501)}), \dots, ((x^{(750)}, y^{(750)}))$
- $(x^{(751)}, y^{(751)}), \dots, ((x^{(1000)}, y^{(1000)}))$

$$temp1 = \sum_{i=1}^{250} (y^{(i)} - h_{\theta}(x^{(i)}))x_j^{(i)}$$

$$temp2 = \sum_{i=256}^{500} (y^{(i)} - h_{\theta}(x^{(i)}))x_j^{(i)}$$

$$temp3 = \sum_{i=501}^{750} (y^{(i)} - h_{\theta}(x^{(i)}))x_j^{(i)}$$

$$temp4 = \sum_{i=751}^{1000} (y^{(i)} - h_{\theta}(x^{(i)}))x_j^{(i)}$$

- Step 2. Calculate temp1 ~ 4
- Step 3. Calculate final results

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Implementation

- **SVMWithSGD**
- **LogisticRegressionWithBFGS**
- **LogisticRegressionWithSGD**
- **LinearRegressionWithSGD**
- **RidgeRegressionWithSGD**
- **LassoWithSGD**

- Cheng-Tao Chu, Sang Kyun Kim, Yi-An Lin, YuanYuan Yu, Gary Bradski, and Andrew Y. Ng, Map-Reduce for Machine Learning on Multicore, NIPS 2006: 281-288

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Speed layer: Apache Storm

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This material is built based on:

- Nathan Marz and James Warren, "Big Data, Principles and Best Practices of Scalable Real-Time Data System", 2015, Manning Publications, ISBN 9781617290343
- Toshiwal, Ankit and Taneja, Siddarth and Shukla, Amit and Ramasamy, Karthik and Patel, Jignesh M. and Kulkarni, Sanjeev and Jackson, Jason and Gade, Krishna and Fu, Maosong and Donham, Jake and Bhagat, Nikunj and Mittal, Sailesh and Ryaboy, Dmitry, "Storm@twitter", Proceedings of the 2014 ACM SIGMOD International Conference on Management of Data, SIGMOD June 22-27, 2014, Snowbird, Utah
- P. Taylor Goetz, and Brian O'Neill, "Storm Blueprints: Patterns for Distributed Real-time Computation" Packt Publishing (March 26, 2014)
- Apache's Storm
 - Open source project
 - <https://storm.apache.org/>

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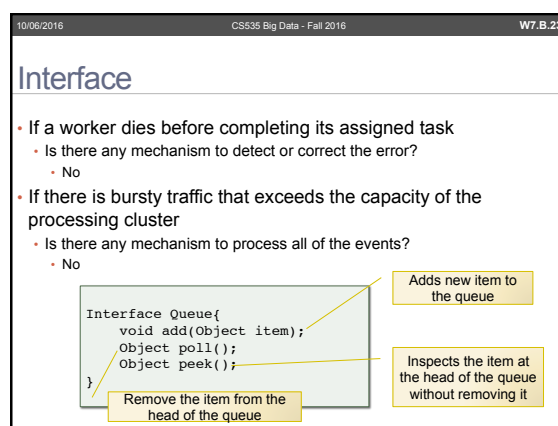
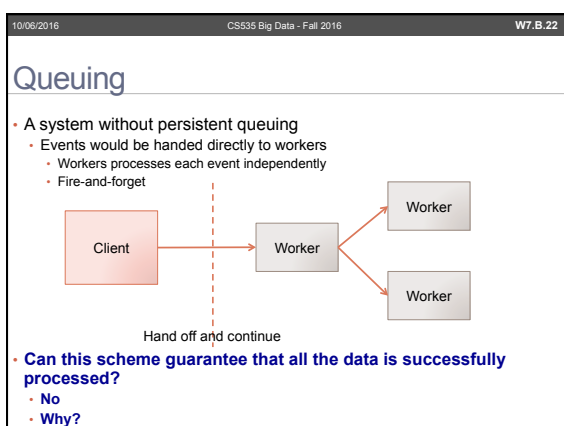
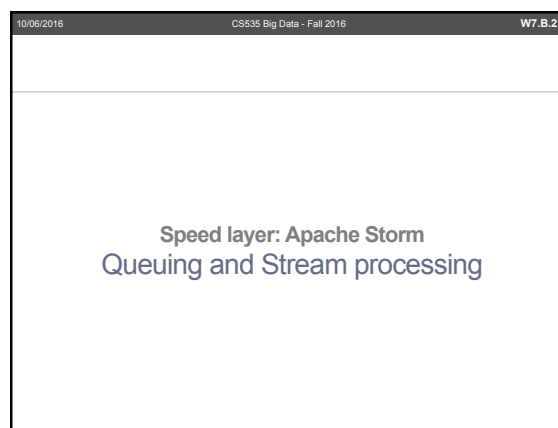
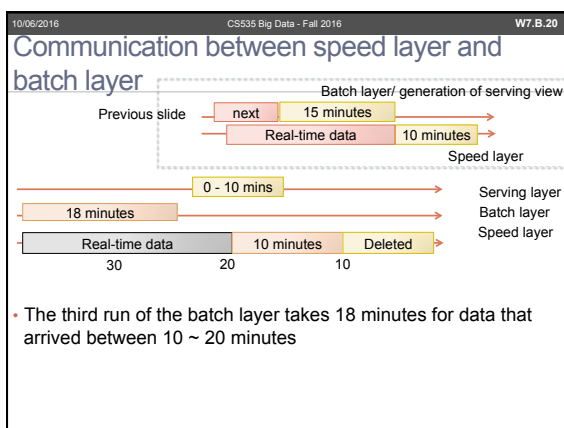
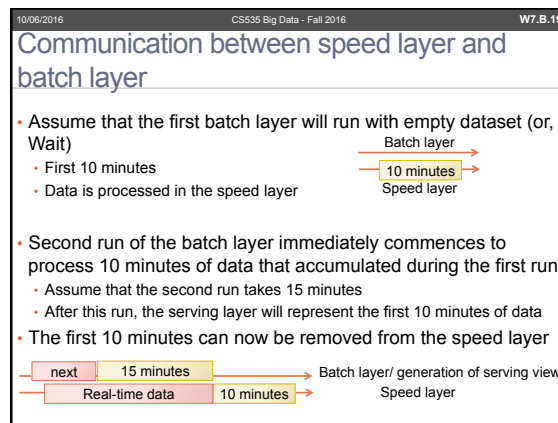
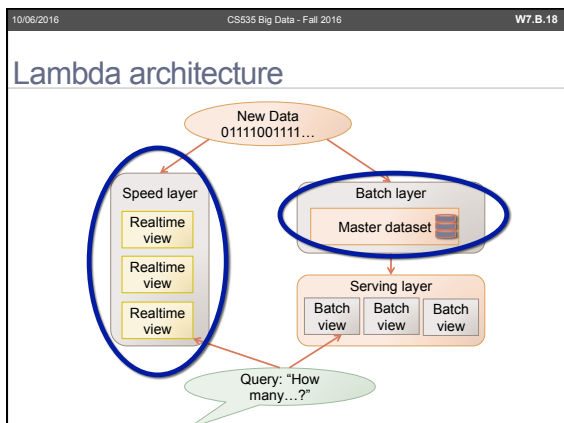
Speed layer: Apache Storm

Speed Layer

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Where are we in the Lambda Architecture?

- We have focused on batch computing in the Lambda Architecture
 - Computing framework
 - Scalable algorithms
- Low-latency update
 - Jobs of the speed layer
 - Incremental computation



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Single consumer queue servers

```

struct Item{
    long id;
    byte[] item;
}
Interface Queue {
    Item get();
    void ack(long id);
    void fail (long id);
}

```

- A generic Item consists of an identifier and a binary payload
- Acknowledges successful processing
- Reports a failure

- When you read an event from the queue
 - The event is not immediately removed
 - The item is returned by the get() function
 - Only when an event is acked, will it be removed from the queue
 - For failed retrieval, another client can retrieve via separate get() function
 - The data is processed **at least once**

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Multiple application with a single queue (1/2)

- What if multiple applications want to consume the same stream?
- Approach 1.**
 - Wrap all the applications within the same consumer

```

graph LR
    Queue[Queue] --> Consumer[Queue Consumer]
    Consumer --> AppA[Application A]
    Consumer --> AppB[Application B]
    Consumer --> AppC[Application C]

```

- Data cannot be processed independently**

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Multiple application with a single queue (2/2)

- Approach 2:**
 - Maintaining a separate queue for each consumer application
 - If you have three applications
 - There are three separate copies of the queue on the queue server
- This increases the load on the queue server

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Multi-consumer queues

- The applications track the consumed/unconsumed status of events from the queue
- Servers**
 - Guarantee that a certain amount of the stream is available
 - E.g. all events from the past 12 hours or the last 50GB of events

```

graph LR
    subgraph Queue [Multi-consumer queue]
        direction LR
        0[0] --- 1[1] --- 2[2] --- 3[3] --- 4[4] --- 5[5] --- Ellipsis[...]
    end
    AppA[Application A] -- "Send 3 items starting from position 4" --> 4
    AppB[Application B] -- "Send 2 items starting from position 2" --> 2

```

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Stream processing

```

graph LR
    Queue[Queue] --> Processor[Stream Processor]
    Processor --> Views[Realtime views]

```

- One-at-a-time**
 - Processes streams with lower latency than micro-batched
 - Queues-and-workers model
- Micro-batched**
 - Small batches of tuples are processed at one time

	One-at-a-time	Micro-batched
Lower latency	Yes	No
Higher throughput	No	Yes
At-least-once semantics	Yes	Yes
Exactly-once semantics	In some cases	Yes
Simpler programming model	Yes	No

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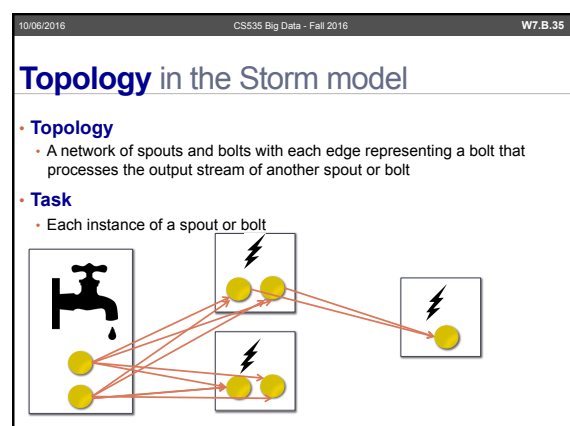
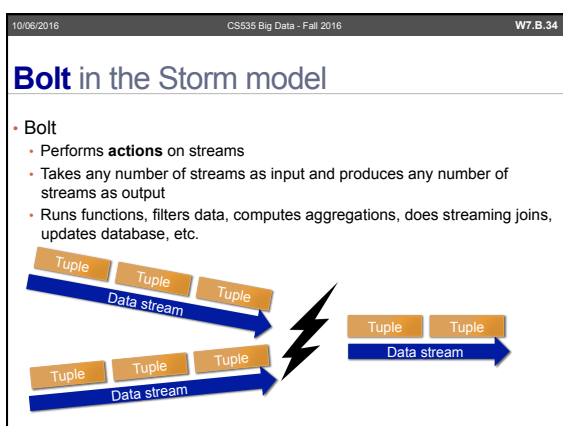
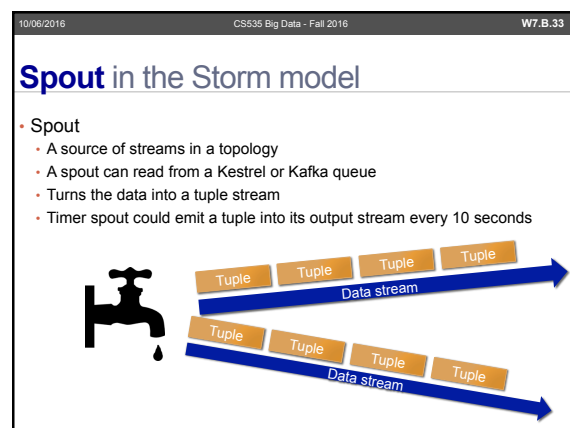
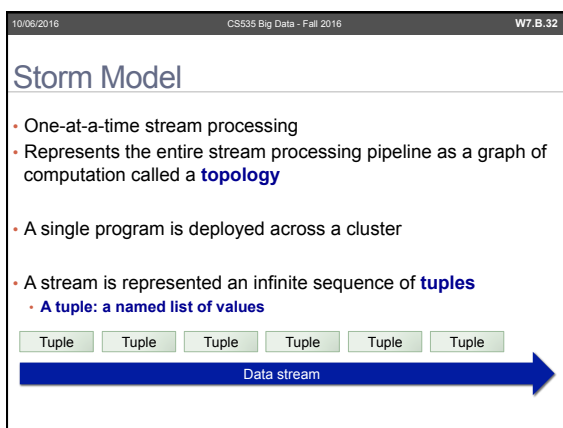
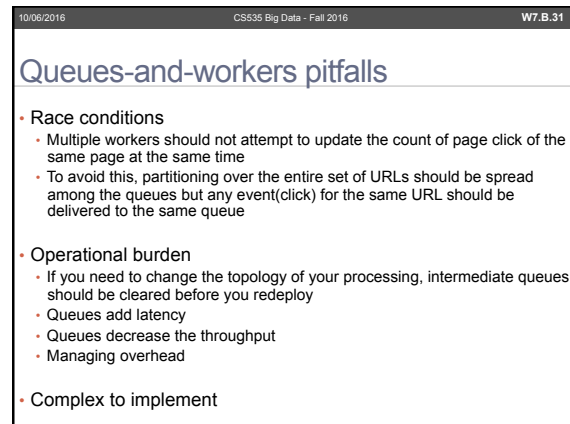
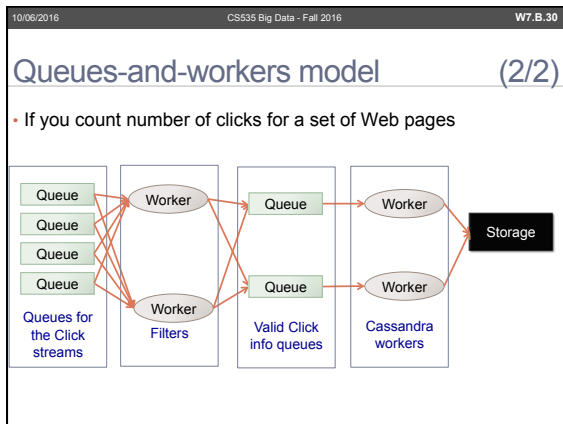
Queues-and-workers model (1/2)

- Common approach to achieve **one-at-a-time** stream processing
 - Divides processing pipeline into worker processes
 - Places queues between them
 - If a worker fails (or restarts) it can continue where it left off by reading from its queue

```

graph LR
    Queue1[Queue] --> Worker1[Worker]
    Queue1 --> Worker2[Worker]
    Queue1 --> Worker3[Worker]
    Worker1 --> Queue2[Queue]
    Worker2 --> Queue2
    Worker3 --> Queue3[Queue]
    Queue2 --> Worker4[Worker]
    Queue3 --> Worker5[Worker]

```



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Storm

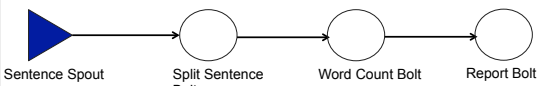
- Scalability
 - Nodes should be added or removed from the Storm cluster without disrupting existing data flows (standing query)
- Resiliency
 - During hardware failures, existing topologies must continue processing with minimal performance impact
- Extensibility
 - External functions should be compatible
- Efficiency
 - Good performance characteristics must be provided for realtime applications
- Easy to Administer
 - Failure or performance issues should be addressed immediately

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Word Count Example

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Word count topology: Sentence Spout



```

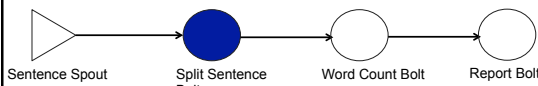
graph LR
    A[Sentence Spout] --> B((Split Sentence Bolt))
    B --> C((Word Count Bolt))
    C --> D((Report Bolt))
  
```

- Sentence spout
 - Emits a stream of single-value tuples continuously with the key name "sentence" and a string value

```
{ "sentence": "my dog has fleas" }
```

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Word count topology: Split Sentence



```

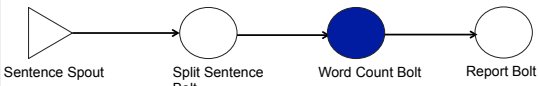
graph LR
    A[Sentence Spout] --> B((Split Sentence Bolt))
    B --> C((Word Count Bolt))
    C --> D((Report Bolt))
  
```

- Split Sentence Bolt
 - Subscribes to the sentence spout's tuple stream

```
{ "word": "my" }
{ "word": "dog" }
{ "word": "has" }
{ "word": "fleas" }
```

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Word count topology: Word Count



```

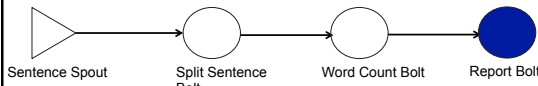
graph LR
    A[Sentence Spout] --> B((Split Sentence Bolt))
    B --> C((Word Count Bolt))
    C --> D((Report Bolt))
  
```

- Word count bolt
 - Subscribes to the output of the SplitSentenceBolt class
 - Keeps a count of how many times it has seen a particular word
 - Whenever it receives a tuple, it will increment the counter and emit

```
{ "word": "dog", "count": 5 }
```

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Word count topology: Report



```

graph LR
    A[Sentence Spout] --> B((Split Sentence Bolt))
    B --> C((Word Count Bolt))
    C --> D((Report Bolt))
  
```

- Report bolt
 - Subscribes to the output of the WordCountBolt class
 - Keeps a count of how many times it has seen a particular word
 - Whenever it receives a tuple, it will update the table and print the contents to the console

```
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SentenceSpout.java

public class SentenceSpout extends BaseRichSpout {
    private SpoutOutputCollector collector;
    private String[] sentences = {
        "my dog has fleas",
        "i like cold beverages",
        "the dog ate my homework",
        "don't have a truck",
        "i don't think i like fleas"
    };

    private int index = 0;
    public void declareOutputFields(OutputFieldsDeclarer declarer) {
        declarer.declare(new Fields("sentence"));
    }
}
```

```
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SentenceSpout.java: Continued

    public void open(Map config, TopologyContext context,
        SpoutOutputCollector collector) {
        this.collector = collector;
    }

    public void nextTuple() {
        this.collector.emit(new Values(sentences[index]));
        index ++;
        if (index >= sentences.length) {
            index = 0;
        }
        Utils.waitForMillis(1);
    }
}
```

```
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SplitSentenceBolt.java

public class SplitSentenceBolt extends BaseRichBolt{
    private OutputCollector collector;
    public void prepare( Map config, TopologyContext context,
        OutputCollector collector)
    {
        this.collector = collector;
    }
    public void execute(Tuple tuple) {
        String sentence = tuple.getStringByField("sentence");
        String[] words = sentence.split(" ");
        for(String word : words) {
            this.collector.emit(new Values(word));
        }
    }
    public void declareOutputFields(OutputFieldsDeclarer declarer) {
        declarer.declare(new Fields("word"));
    }
}
```

```
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WordCountBolt.java

public class WordCountBolt extends BaseRichBolt{
    private OutputCollector collector;
    private HashMap < String, Long > counts = null;
    public void prepare( Map config, TopologyContext context,
        OutputCollector collector) {
        this.collector = collector;
        this.counts = new HashMap < String, Long >();
    }
    public void execute( Tuple tuple) {
        String word = tuple.getStringByField("word");

        Long count = this.counts.get(word);
        if(count == null){ count = 0; }
        count ++;
        this.counts.put( word, count);
        this.collector.emit(new Values(word, count));
    }
    public void declareOutputFields( OutputFieldsDeclarer declarer) {
        declarer.declare(new Fields("word", "count"));
    }
}
```