INDIAN INSTITUTE OF INFORMATION TECHNOLOGY

Dharwad
ज्ञानेन विकासः

Big Data Analytics and Ubiquitous Computing

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PDPM
Indian Institute of Information Technology, Design and Manufacturing, Jabalpur

The Alan Turing Institute

Big Data Analytics

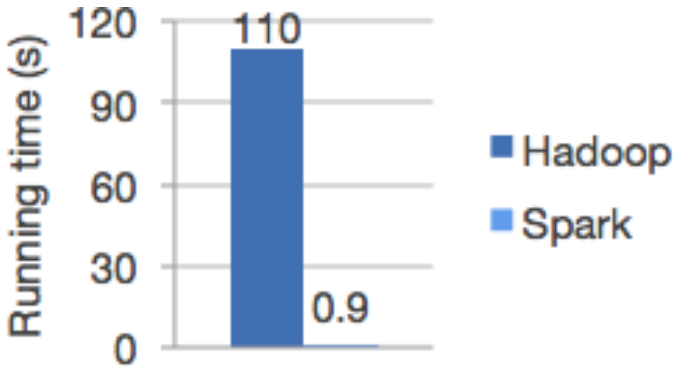
- **Big Data Analytics**
  1. **Big Data**
  2. **Spark: Big Data Analytics**
  3. **Resilient Distributed Datasets (RDD)**
  4. **Spark libraries (SQL, DataFrames, MLlib for machine learning, GraphX, and Streaming)**
  5. **PFP: Parallel FP-Growth**
- Ubiquitous Computing

Big Data

- Big data can be described by the following characteristics:
  - Volume: size large than terabytes and petabytes
  - Variety: type and nature, structured, semi-structured or unstructured
  - Velocity: speed of generation and processing to meet the demands
  - Veracity: the data quality and the data value
  - Value: Useful or not useful
- The main components and ecosystem of Big Data
  - Data Analytics: data mining, machine learning and natural language processing
  - Technologies: Business Intelligence, Cloud computing & Databases
  - Visualization: Charts, Graphs etc.

Apache Spark

- Unified analytics engine for large-scale data processing.
- Speed: Run workloads 100x faster.
- Both batch and streaming data, using Directed Acyclic Graph (DAG) scheduler, a query optimizer, and a physical execution engine.
- Ease of Use: Write applications quickly in Java, Scala, Python, R, and SQL.
- Spark offers 80+ high-level operators to build parallel apps.



https://spark.apache.org/

Spark: Unified Big Data Analytics

- New applications of Big data workloads on Unified Engine of
  - Streaming, Batch, and Interactive.
- Composability in programming libraries for big data and encourages development of interoperable libraries
- Combining the SQL, machine learning, and streaming libraries in Spark

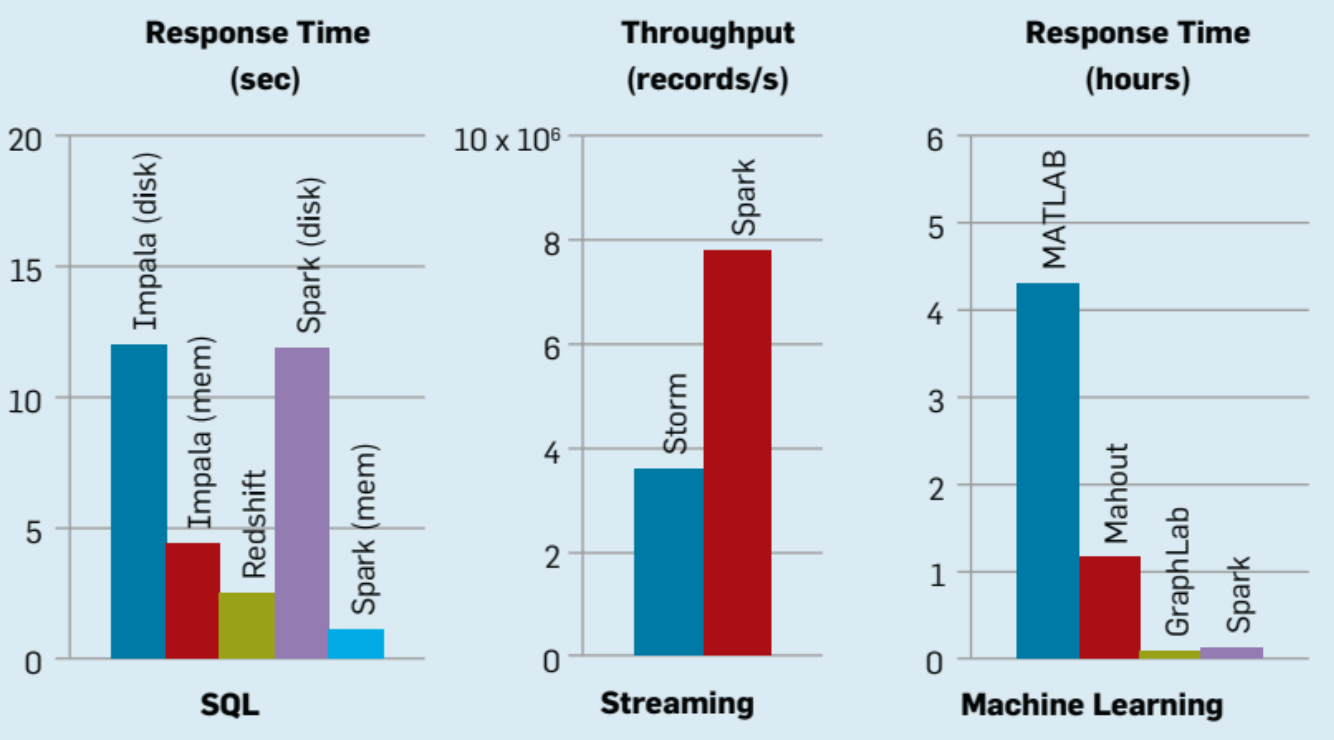
```
// Load historical data as an RDD using Spark SQL
val trainingData = sql(
   "SELECT location, language FROM old_tweets")

// Train a K-means model using MLlib
val model = new KMeans()
   .setFeaturesCol("location")
   .setPredictionCol("language")
   .fit(trainingData)
// Apply the model to new tweets in a stream
TwitterUtils.createStream(...)
      .map(tweet => model.predict(tweet.location))
```

Zaharia, Matei, et al. "Apache spark: a unified engine for big data processing." *Communications of the ACM* 59.11 (2016): 56-65.

Spark: Unified Big Data Analytics

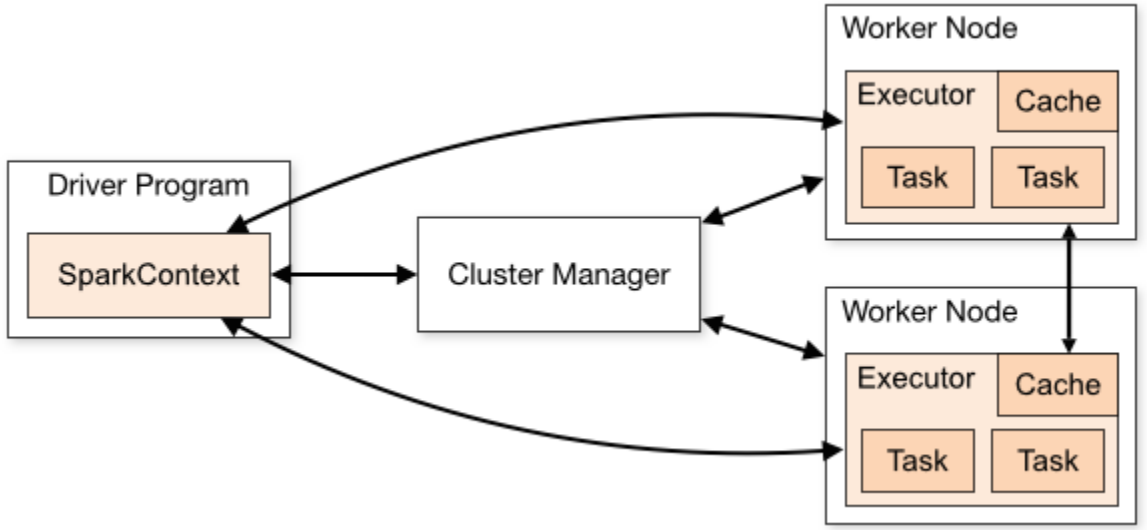
- Spark has MapReduce programming model with extended data-sharing abstraction called "Resilient Distributed Datasets," or RDDs.



Zaharia, Matei, et al. "Apache spark: a unified engine for big data processing." *Communications of the ACM* 59.11 (2016): 56-65.

Spark Architecture

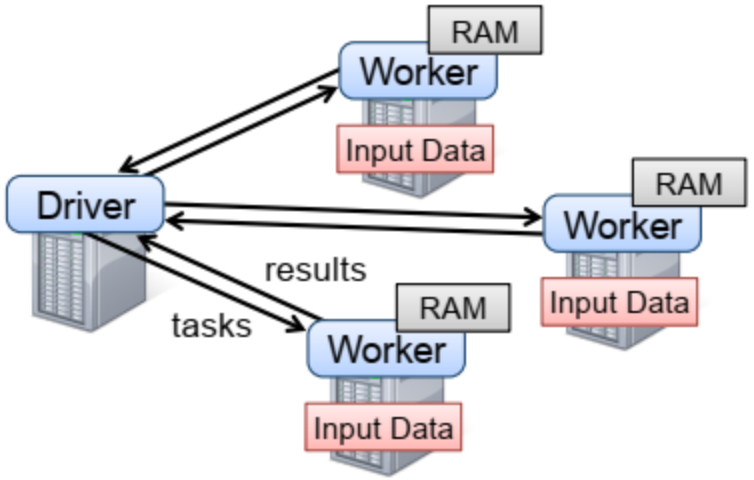
- Spark works on the popular Master-Slave architecture.
- Cluster works with a single master and multiple slaves.
- The Spark architecture depends upon two abstractions:
  - Resilient Distributed Dataset (RDD)
  - Directed Acyclic Graph (DAG)



https://spark.apache.org/docs/latest/cluster-overview.html

Resilient Distributed Datasets (RDD)

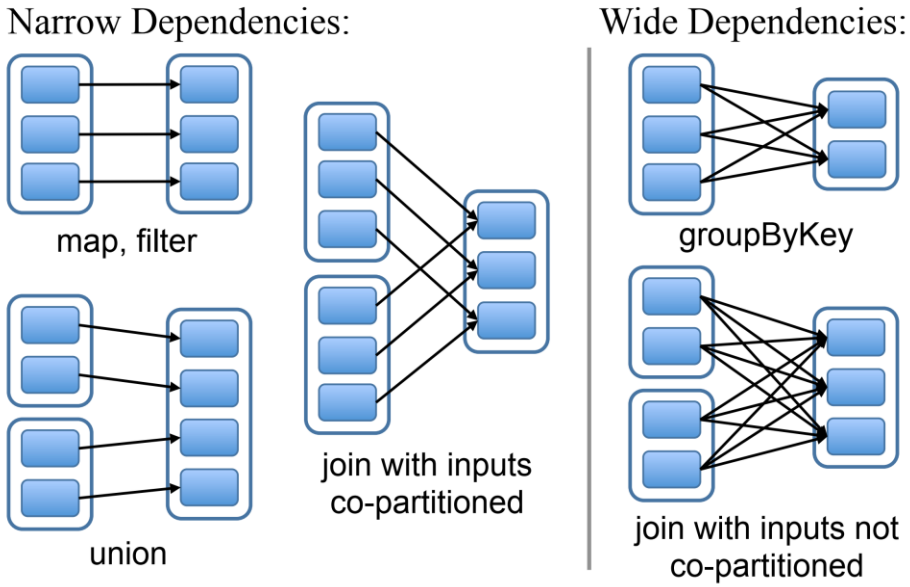
- A distributed memory abstraction: perform in-memory computations on large clusters
- Keeping data in memory can improve performance
- Spark runtime: Driver program launches multiple workers that read data blocks from a distributed file system and can persist computed RDD partitions in memory.



Zaharia, Matei, et al. "Resilient distributed datasets: A fault-tolerant abstraction for in-memory cluster computing." *Presented as part of the 9th {USENIX} Symposium on Networked Systems Design and Implementation ({NSDI} 12)*. 2012.

Resilient Distributed Datasets (RDD)

- Each box is an RDD, with partitions as shaded rectangles.
- *narrow* dependencies, where each partition of the parent RDD is used by at most one partition of the child RDD,
- *wide* dependencies, where multiple child partitions may depend on it.



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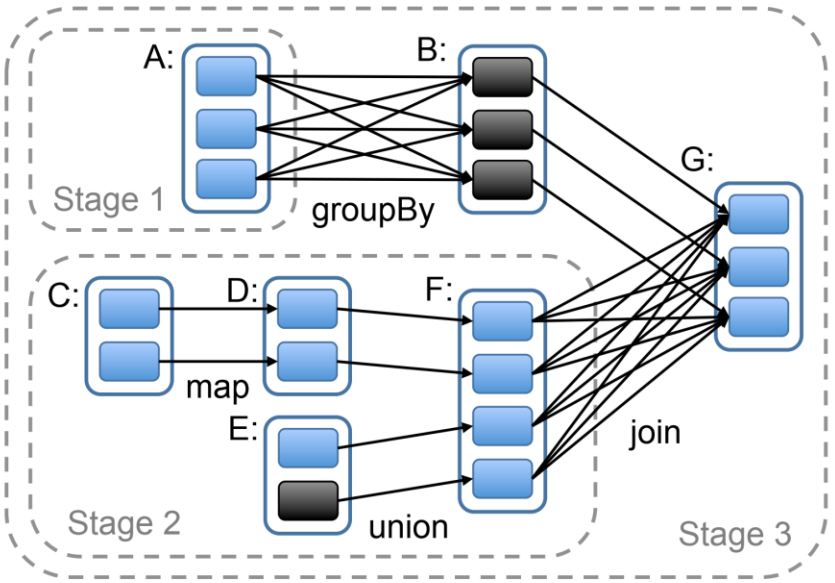
Resilient Distributed Datasets (RDD)

- Direct Acyclic Graph (DAG) to perform a sequence of computations
- Each node is an RDD partition,
- Run an action (*e.g.*, *count* or *save*) on an RDD, the scheduler examines that RDD's lineage graph to build a DAG of *stages* to execute.
- Each stage contains with narrow dependencies
- The boundaries of the stages are the shuffle operations required for wide dependencies.
- Scheduler computes missing partitions until it computed RDD.



Zaharia, Matei, et al. "Resilient distributed datasets: A fault-tolerant abstraction for in-memory cluster computing." *Presented as part of the 9th {USENIX} Symposium on Networked Systems Design and Implementation ({NSDI} 12)*. 2012.

Apache Spark

- Combine SQL, streaming, and complex analytics. Spark libraries
  - SQL and DataFrames,
  - MLlib for machine learning,
  - GraphX, and
  - Spark Streaming.
- Spark runs on Hadoop, Apache Mesos, Kubernetes, standalone, or in the cloud.
- Run Spark using its standalone cluster mode, on EC2, on Hadoop YARN, on Mesos, or on Kubernetes.
- Access data in HDFS, Alluxio, Apache Cassandra, Apache HBase, Apache Hive, and hundreds of other data sources.

https://spark.apache.org/

Spark Code Example

- Word Count

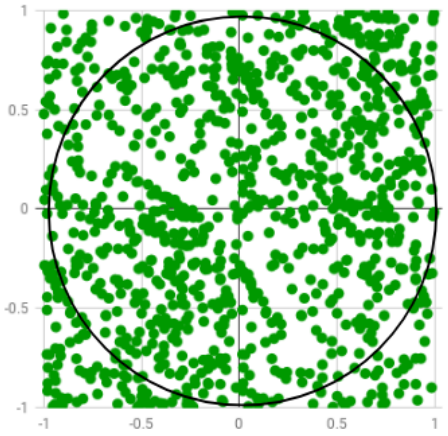
```
JavaRDD<String> textFile = sc.textFile("hdfs://...");
JavaPairRDD<String, Integer> counts = textFile
    .flatMap(s -> Arrays.asList(s.split(" ")).iterator())
    .mapToPair(word -> new Tuple2<>(word, 1))
    .reduceByKey((a, b) -> a + b);
counts.saveAsTextFile("hdfs://...");
```

- Pi Estimation

```
List<Integer> l = new ArrayList<>(NUM_SAMPLES);
for (int i = 0; i < NUM_SAMPLES; i++) {
  l.add(i);
}

long count = sc.parallelize(l).filter(i -> {
  double x = Math.random();
  double y = Math.random();
  return x*x + y*y < 1;
}).count();
System.out.println("Pi is roughly " + 4.0 * count / NUM_SAMPLES);
```

$$\text{Pi} = 4 \times \frac{number\ of\ random\ point\ inside\ the\ circle}{number\ of\ random\ point\ inside\ the\ square}$$



Spark SQL

- Working with structured data.
- Integrated: SQL queries with Spark programs.

```
results = spark.sql("SELECT * FROM people")
names = results.map(lambda p: p.name)
```

Apply functions to results of SQL queries.

- Uniform Data Access: Connect to data sources, including Hive, Avro, Parquet, ORC, JSON, and JDBC.

```
spark.read.json("s3n://…").registerTempTable("json")
results = spark.sql("""SELECT * FROM people JOIN json …""")
```

- Query and join different data sources
- Hive Integration Spark HiveQL
- Standard Connectivity: Connect through JDBC or ODBC.
- Business intelligence tools to query big data.

https://spark.apache.org/sql/

DataFrame API Examples

- Collection of data organized into named columns
- Use DataFrame API to perform various relational operations
- Automatically optimized by Spark's built-in optimizer

```
// Creates a DataFrame having a single column named "line"
JavaRDD<String> textFile = sc.textFile("hdfs://...");
JavaRDD<Row> rowRDD = textFile.map(RowFactory::create);
List<StructField> fields = Arrays.asList(
  DataTypes.createStructField("line", DataTypes.StringType, true));
StructType schema = DataTypes.createStructType(fields);
DataFrame df = sqlContext.createDataFrame(rowRDD, schema);

DataFrame errors = df.filter(col("line").like("%ERROR%"));
// Counts all the errors
errors.count();
// Counts errors mentioning MySQL
errors.filter(col("line").like("%MySQL%")).count();
// Fetches the MySQL errors as an array of strings
errors.filter(col("line").like("%MySQL%")).collect();
```

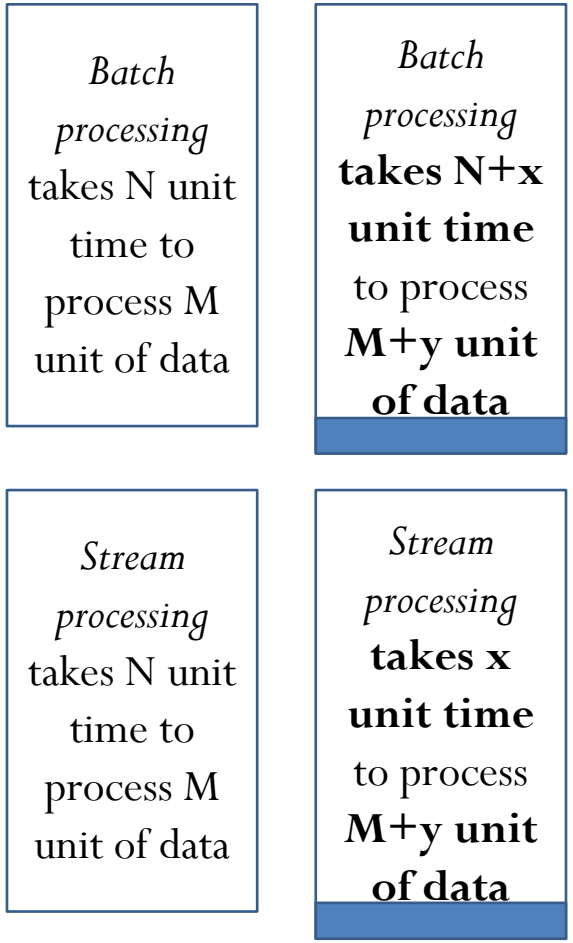
Spark Streaming

- Build scalable fault-tolerant streaming applications.
- Write streaming jobs -- Same Way -- Write batch jobs
  - Counting tweets on a sliding window

```
TwitterUtils.createStream(…)
.filter(_.getText.contains("Spark"))
.countByWindow(Seconds(5))
```

- Reuse the same code for batch processing
  - Find words with higher frequency than historic data:

```
stream.join(historicCounts).filter {
  case (word, (curCount, oldCount)) =>
    curCount > oldCount
}
```



https://spark.apache.org/streaming/

Spark GraphX

- Spark's API for graphs and graph-parallel computation

```
graph = Graph(vertices, edges)
messages = spark.textFile("hdfs://…")
graph2 = graph.joinVertices(messages) {
  (id, vertex, msg) => …
}
```

- Fast Speed for graph algorithms
- GraphX graph algorithms
  - PageRank
  - Connected components
  - Label propagation
  - SVD++
  - Strongly connected components
  - Triangle count

https://spark.apache.org/graphx/

Spark MLlib

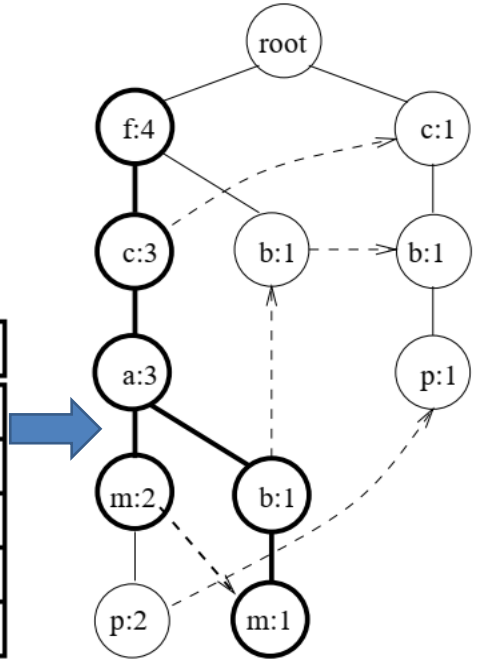
- Spark's scalable machine learning library
- Spark MLlib algorithms
  - Classification: logistic regression, naive Bayes,…
  - Regression: generalized linear regression, survival regression,…
  - Decision trees, Random forests, and Gradient-boosted trees
  - Recommendation: Alternating Least Squares (ALS)
  - Clustering: K-means, Gaussian mixtures (GMMs),…
  - Topic modeling: Latent Dirichlet Allocation (LDA)
  - **Frequent itemsets, Association rules, and Sequential pattern mining**

https://spark.apache.org/graphx/

FP-Growth for recommendation

- "FP" stands for Frequent Pattern in a Dataset of transactions
  1. calculate item frequencies and identify frequent items,
  2. a suffix tree (FP-tree) structure to encode transactions, and
  3. frequent itemsets can be extracted from the FP-tree.
- Input: Transaction database
- Intermediate Output: FP-Tree
- Output: {f, c, a → a, m p}, {f, c, a → b, m}

TID	Items Bought	(Ordered) Frequent Items
100	f, a, c, d, g, i, m, p	f, c, a, m, p
200	a, b, c, f, l, m, o	f, c, a, b, m
300	b, f, h, j, o	f, b
400	b, c, k, s, p	c, b, p
500	a, f, c, e, l, p, m, n	f, c, a, m, p



Han Jiawei, Jian Pei, and Yiwen Yin. "Mining frequent patterns without candidate generation." *ACM SIGMOD Record* 29.2 (2000): 1-12.

PFP: Parallel FP-Growth

- In Spark ML-Library (MLLib), a parallel version of FP-growth called PFP: Parallel FP-Growth
- PFP distributes the work of growing FP-trees based on the suffixes of transactions.
- More scalable than a single-machine implementation.
- PFP partitions computation, where each machine executes an independent group of mining tasks

Li, Haoyuan, et al. "PFP: Parallel FP-Growth for query recommendation." *Proceedings of the 2008 ACM Conference on Recommender systems*. 2008.

PFP: Parallel FP-Growth

Example of MapReduce FP-Growth: Five transactions composed of lower-case alphabets representing items

Map inputs (transactions) key="": value	Sorted transactions (with infrequent items eliminated)	Map outputs (conditional transactions) key: value
f a c d g i m p	f c a m p	p: f c a m m: f c a a: f c c: f
a b c f l m o	f c a b m	m: f c a b b: f c a a: f c c: f
b f h j o	f b	b: f
b c k s p	c b p	p: c b b: c
a f c e l p m n	f c a m p	p: f c a m m: f c a a: f c c: f

Reduce inputs (conditional databases) key: value		Conditional FP–trees
p:	{ f c a m / f c a m / c b }	{(c:3)} | p
m:	{ f c a / f c a / f c a b }	{ (f:3, c:3, a:3) } | m
b:	{ f c a / f / c }	{} | b
a:	{ f c / f c / f c }	{ (f:3, c:3) } | a
c:	{ f / f / f }	{ (f:3) } | c

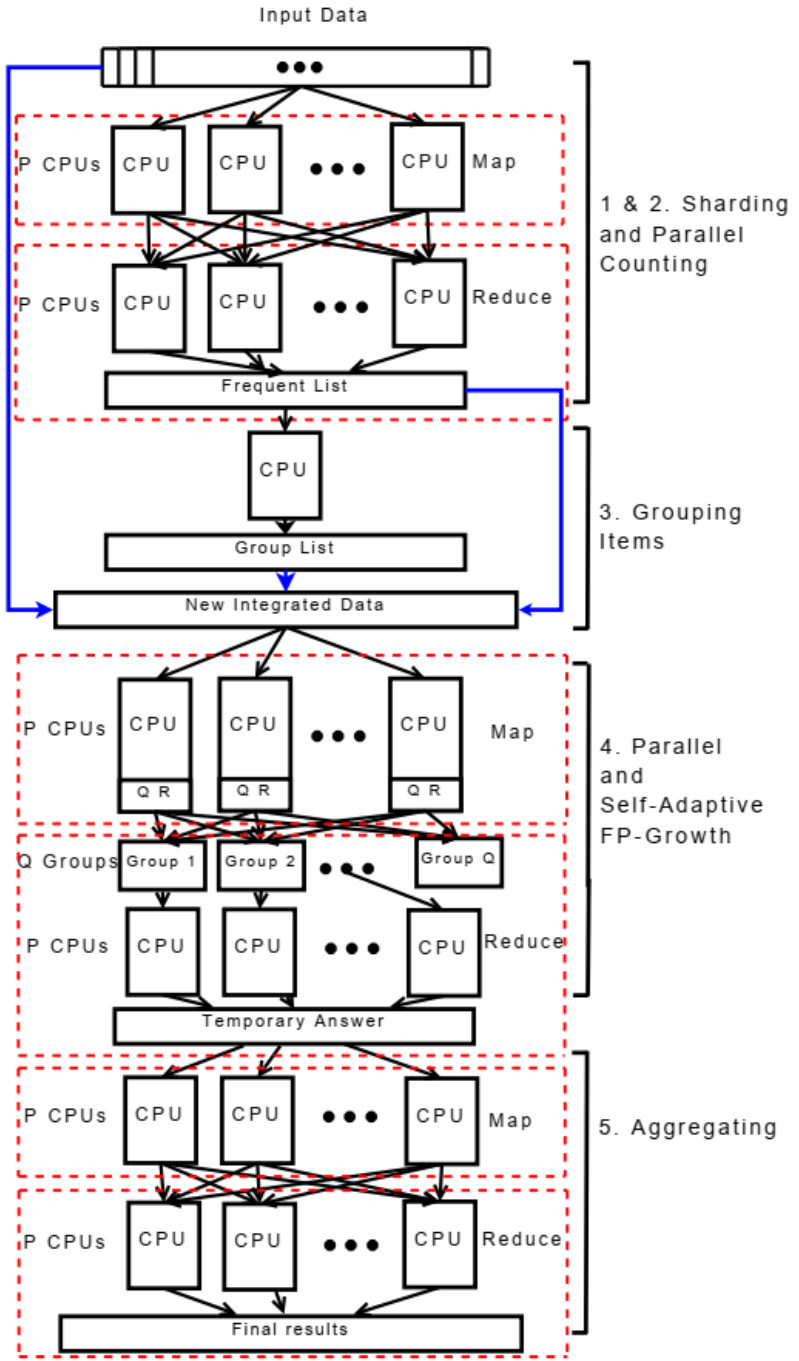
Li, Haoyuan, et al. "PFP: Parallel FP-Growth for query recommendation." *Proceedings of the 2008 ACM Conference on Recommender systems*. 2008.

- **Sharding:** Divide DB into successive parts and storing the parts (as a Shard) on P different computers.
- **Parallel Counting:** MapReduce counts the support of all items that appear in DB. Each mapper inputs one shard of DB. The result is stored in F-list.
- **Grouping Items:** Dividing all the items on F-List into Q groups of a list (G-list).
- **Parallel FP-Growth:** A MapReduce

  - Mapper: Each mapper uses a Shard. It reads a transaction in the G-list and outputs one or more key-value pairs, where each key is a *group-id* and value is a **group-dependent transaction**.

  - For each *group-id*, the MapReduce groups all group-dependent transactions into a shard.

  - Reducer: Each reducer processes one or more group-dependent Shard. For each shard, a reducer builds a local FP-Tree and discover patterns.
- **Aggregating:** Aggregate the results generated as final result.



Li, Haoyuan, et al. "PFP: Parallel FP-Growth for query recommendation." *ACM Conf. on Recommender systems*. 2008.

PFP: Parallel FP-Growth

- FP-Growth implementation takes the following (hyper-)parameters
  - minSupport: the minimum support for an itemset to be identified as frequent e.g., if an item appears 3 out of 5 transactions, it has a support of 3/5=0.6.
  - minConfidence: minimum confidence for generating Association Rule e.g., if in the transactions itemset X appears 4 times, X andY co-occur only 2 times, the confidence for the rule X =>Y is then 2/4 = 0.5.
  - numPartitions: the number of partitions used to distribute the work.
- FP-Growth model provides:
  - freqItemsets: frequent itemsets in the format of DataFrame("items"[Array], "freq"[Long])
  - associationRules: association rules generated with confidence above minConfidence, in the format of DataFrame("antecedent"[Array], "consequent"[Array], "confidence"[Double]).

PFP: Parallel FP-Growth

```
import java.util.Arrays;
import java.util.List;

import org.apache.spark.ml.fpm.FPGrowth;
import org.apache.spark.ml.fpm.FPGrowthModel;
import org.apache.spark.sql.Dataset;
import org.apache.spark.sql.Row;
import org.apache.spark.sql.RowFactory;
import org.apache.spark.sql.SparkSession;
import org.apache.spark.sql.types.*;

List<Row> data = Arrays.asList(
  RowFactory.create(Arrays.asList("1 2 5".split(" "))),
  RowFactory.create(Arrays.asList("1 2 3 5".split(" "))),
  RowFactory.create(Arrays.asList("1 2".split(" ")))
);
StructType schema = new StructType(new StructField[]{ new StructField(
  "items", new ArrayType(DataTypes.StringType, true), false, Metadata.empty())
});
Dataset<Row> itemsDF = spark.createDataFrame(data, schema);

FPGrowthModel model = new FPGrowth()
  .setItemsCol("items")
  .setMinSupport(0.5)
  .setMinConfidence(0.6)
  .fit(itemsDF);

// Display frequent itemsets.
model.freqItemsets().show();

// Display generated association rules.
model.associationRules().show();

// transform examines the input items against all the association rules and summarize the
// consequents as prediction
model.transform(itemsDF).show();
```

Ubiquitous Computing

- Big Data Analytics (Apache Spark (SQL, Mllib, GraphX))
- **Ubiquitous Computing**
  1. **Edge Computing**
  2. **Cloudlet**
  3. **Fog computing**
  4. **Internet of Things (IoT)**
  5. **Virtualization**
  6. **Virtual Conferencing**
  7. **Virtual Events (2D, 3D, and Hybrid)**

Ubiquitous computing

- Mark Weiser: Three basic ubiquitous computing devices:
  - Tabs: a wearable device that is approx in centimeters
  - Pads: a hand-held device that is approximately a decimeter in size
  - Boards: an interactive larger display device that is approximately a meter in size
- computing is made to appear anytime and everywhere
- any device, in any location, and in any format

Weiser, Mark. "The computer for the 21st century." *ACM SIGMOBILE mobile computing and communications review* 3.3 (1999): 3-11.
https://en.wikipedia.org/wiki/Ubiquitous_computing

Edge computing

- Distributed computing paradigm
- Computation and data storage closer to the user location
- Improve response times and save bandwidth
- Cloud computing operates on big data, whereas Edge computing operates on "instant data"
- Content Delivery Network or Content Distribution Network (CDN) (Refer to Unit 4)
- Akamai CDN (Refer to Unit 4)
- Akamai-Facebook's Photo-Serving Stack (Refer to Unit 4)

https://en.wikipedia.org/wiki/Edge_computing

Cloudlet

- First coined by Mahadev Satyanarayanan (Satya), Victor Bahl, Ramón Cáceres, and Nigel Davie
- It is a mobility-enhanced small-scale cloud datacenter that is located at the edge of the Internet.
- It work as a *data center in a box* which *brings the cloud closer.*
- Support resource-intensive and interactive mobile applications by providing powerful computing resources to mobile devices with lower latency.

https://en.wikipedia.org/wiki/Cloudlet

Fog computing

- Architecture that distributes computing, storage, control and networking functions closer to the users along a cloud-to-thing.
- Fog computing is often erroneously called edge computing, but there are key differences.
- Fog works with the cloud, whereas edge is defined by the exclusion of cloud.
- Fog is hierarchical where edge tends to be limited to a small number of layers.
- Cloud computing deal with Big Data, whereas Fog computing deals with real-time data generated by sensors or users.

[1] IEEE Standard Association. "IEEE 1934-2018-IEEE Standard for adoption of OpenFog reference architecture for fog computing." (2018).
https://en.wikipedia.org/wiki/Fog_computing

Internet of Things (IoT)

- The network of physical objects —"things"— embedded with sensors, software, and other technologies for the purpose of connecting and exchanging data with other devices and systems over the Internet.
- Example:
  - "Smart Home" devices and appliances,
  - "Smart city" equipment and facilities,
- Real-Time Data Analytics
- *Information explosion* or *Data Deluge*
  - due to *data flood* or *information flood*
  - ever-increasing amount of electronic data exchanged per time unit
  - unmanageable amounts of data growth V/S power of data processing

https://en.wikipedia.org/wiki/Internet_of_things

Virtualization

- Virtual computer hardware platforms, storage devices, and computer network resources.
- *Hardware virtualization* or *platform virtualization* refers to the creation of a Virtual Machine (VM).
  - Full virtualization – complete simulation of the actual hardware to allow software environments, guest operating system and its apps.
  - Paravirtualization – the guest apps are executed in their own isolated domains.
- Application virtualization and Workspace virtualization: isolating individual apps from the underlying OS and other apps
- Service virtualization: emulating the behavior of API, Cloud and SOA

https://en.wikipedia.org/wiki/Virtualization

Virtualization

- Memory virtualization: aggregating RAM resources from networked systems into a single memory pool
- Virtual memory: giving an app the impression that it has contiguous working memory, isolating the underlying physical memory
- Storage virtualization: the process of completely abstracting logical storage from physical storage
- Distributed file system: any file system that allows access to files from multiple hosts sharing via a computer network
- Virtual file system: an abstraction layer on top of a more concrete file system
- Storage hypervisor: combines physical storage resources into one or more flexible pools of logical storage

https://en.wikipedia.org/wiki/Virtualization

Virtualization

- Virtual disk: emulates a disk drive such as a hard disk drive or optical disk drive
- Data virtualization: the presentation of data as an abstract layer, independent of underlying database systems, structures and storage
- Database virtualization: the decoupling of the database layer, which lies between the storage and application layers
- Network virtualization: creation of a virtualized network addressing space within or across network subnets
- Virtual private network (VPN): replaces the actual wire or other physical media in a network with an abstract layer

https://en.wikipedia.org/wiki/Virtualization

Virtual Conferencing

- Teleconference: Phone lines, Landlines or Cellular devices
- Video conference:
  - Webcam, Microphone, Speaker, Internet
  - hardware, software, devices is dedicated for this
- Web Conference: Internet and Cloud supported
  - Web 2.0
  - Well-Known: Google Meet, Skype, and Microsoft Team
  - Multi-Communications from Many sender to Many receivers
  - Webinars ("web seminars"), Webcasts (live media presentation), Podcast (audio presentation), and web meetings
  - **Virtual Events**

https://en.wikipedia.org/wiki/Internet_of_things

Virtual Events

- An online event involves people interacting in a virtual environment on the web, instead of physical meeting.
- Multi-session online events often feature webinars and webcasts.
- Aim to create similar experience as physical meeting.
- Live-streaming the event online or on-demand video.
- Issues
  - Echo of voice
  - Audio and Videography logistics
  - Network Bandwidth of conferencing server and users

https://en.wikipedia.org/wiki/Virtual_event

2D Virtual Events: Edited Collage

2D Virtual Events: Virtual Degree

2D Virtual Events: Virtual Address

3D Virtual Event: Live Video

[Virtual HLF 2020 - Heidelberg Laureate Forum]

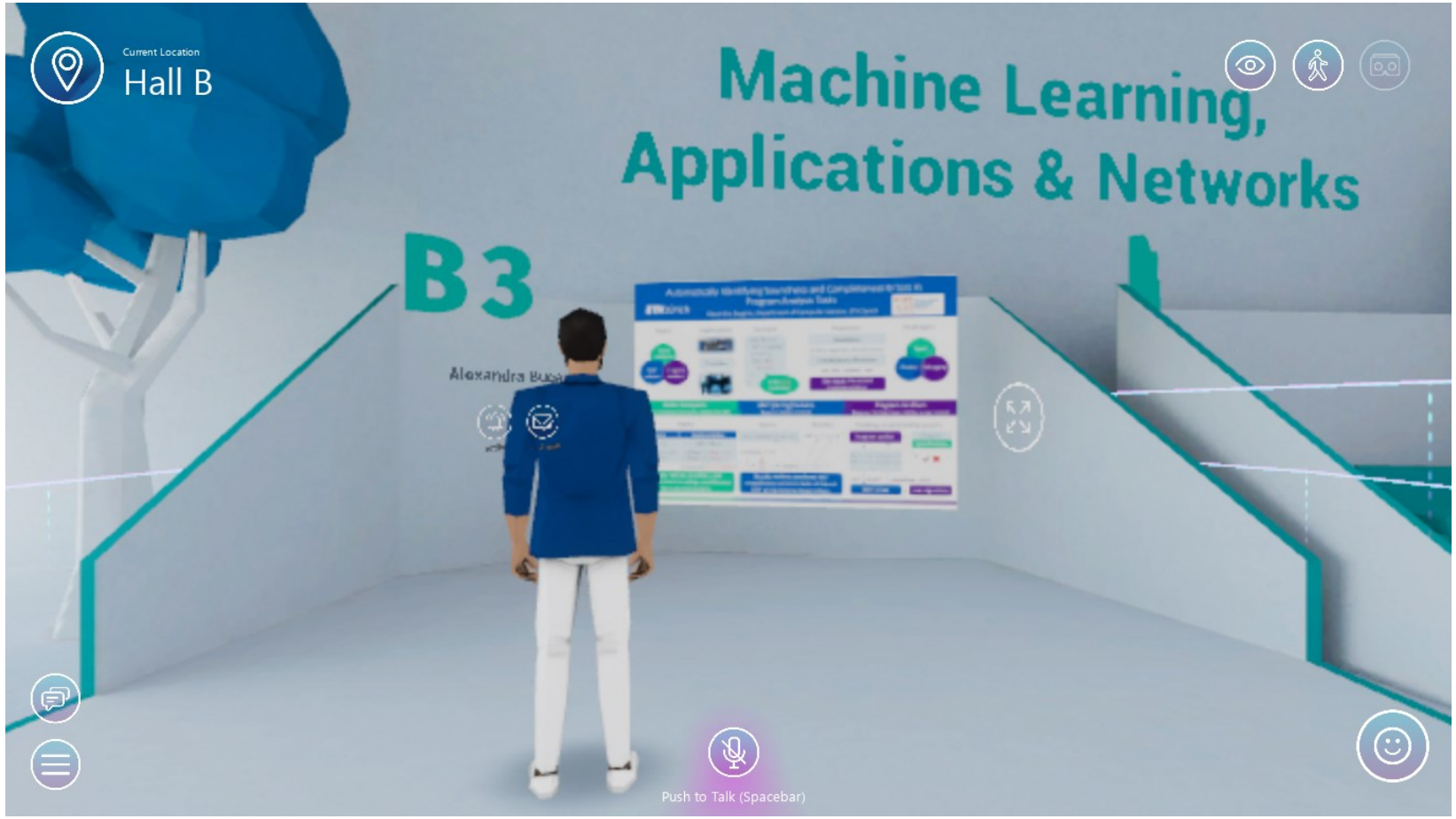
3D Virtual Event:

[Virtual HLF 2020 - Heidelberg Laureate Forum]

3D Virtual Event: Poster Sessions

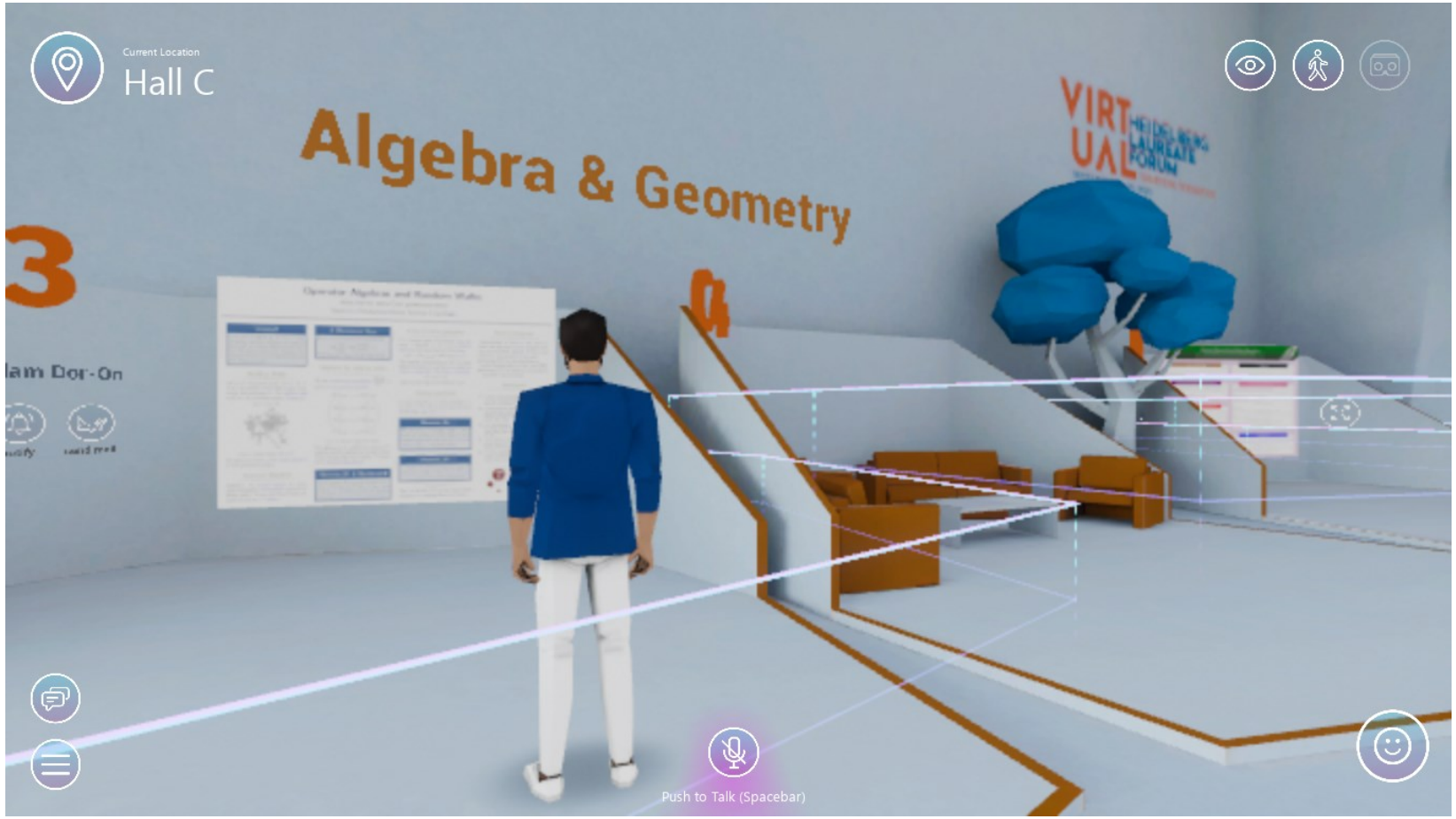
[Virtual HLF 2020 - Heidelberg Laureate Forum]

3D Virtual Event: Poster Sessions



Virtual HLF 2020 - Heidelberg Laureate Forum

3D Virtual Event: Poster Sessions



[Virtual HLF 2020 - Heidelberg Laureate Forum]

3D Virtual Event: Poster Sessions

Virtual HLF 2020 - Heidelberg Laureate Forum

3D Virtual Event: Virtual Gathering

Virtual HLF 2020 - Heidelberg Laureate Forum

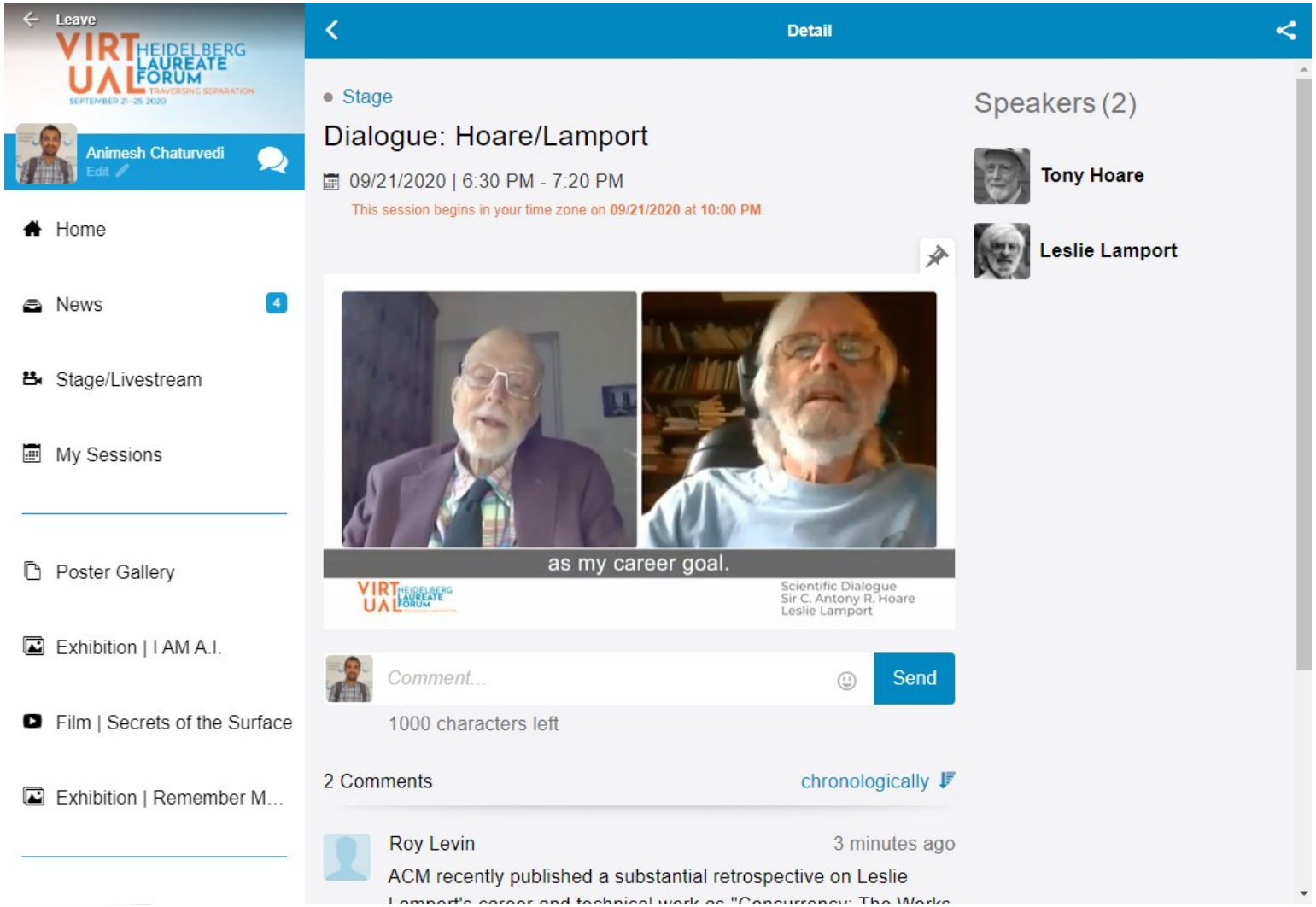
3D Virtual Event: Recreations

Virtual HLF 2020 - Heidelberg Laureate Forum

3D Virtual Event: Virtual Dancing

Virtual HLF 2020 - Heidelberg Laureate Forum

Live Streaming



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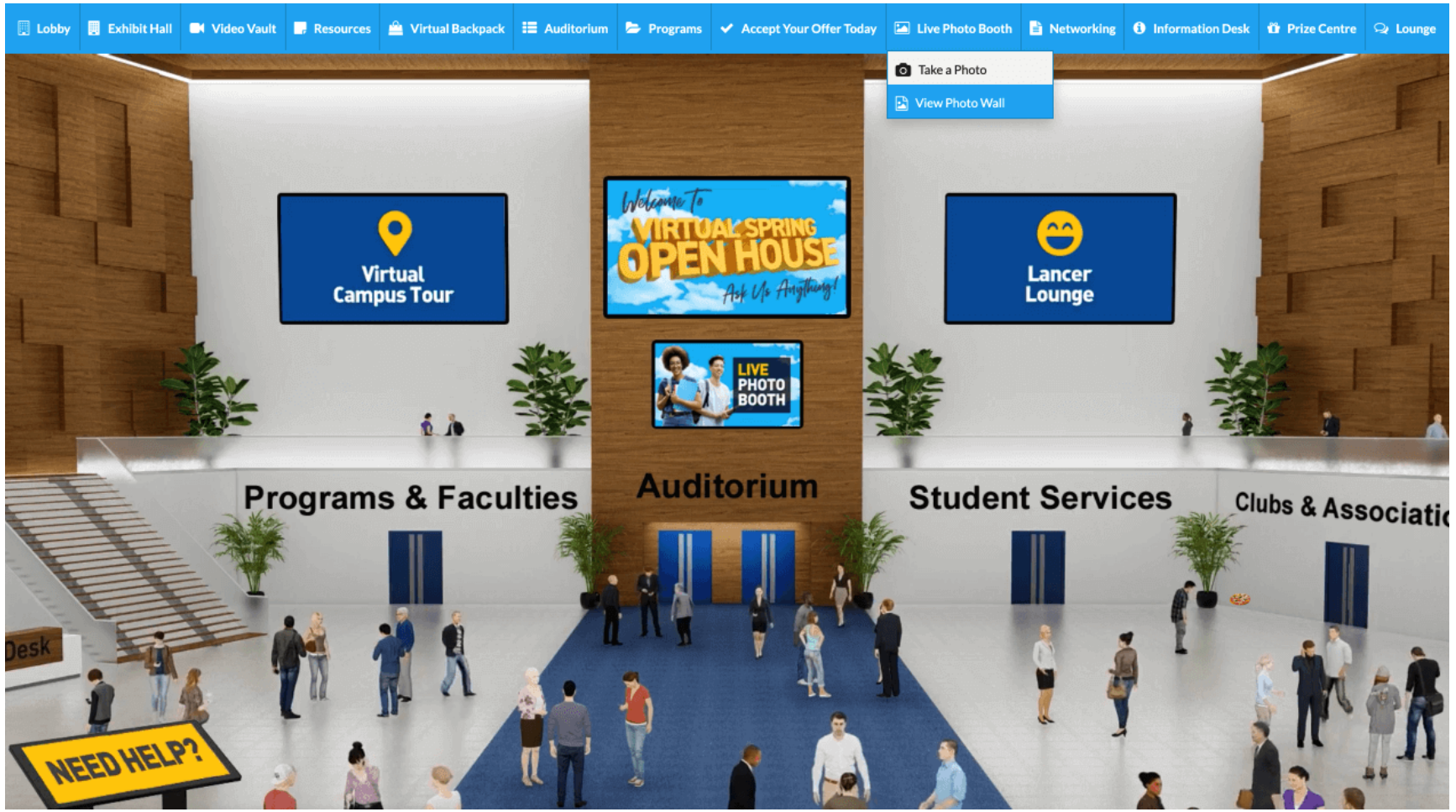
Hybrid Event

- Combines a “physical" in-person event with a "virtual" online component
- Tradeshow, Conference, Seminar, Workshop, Convocation

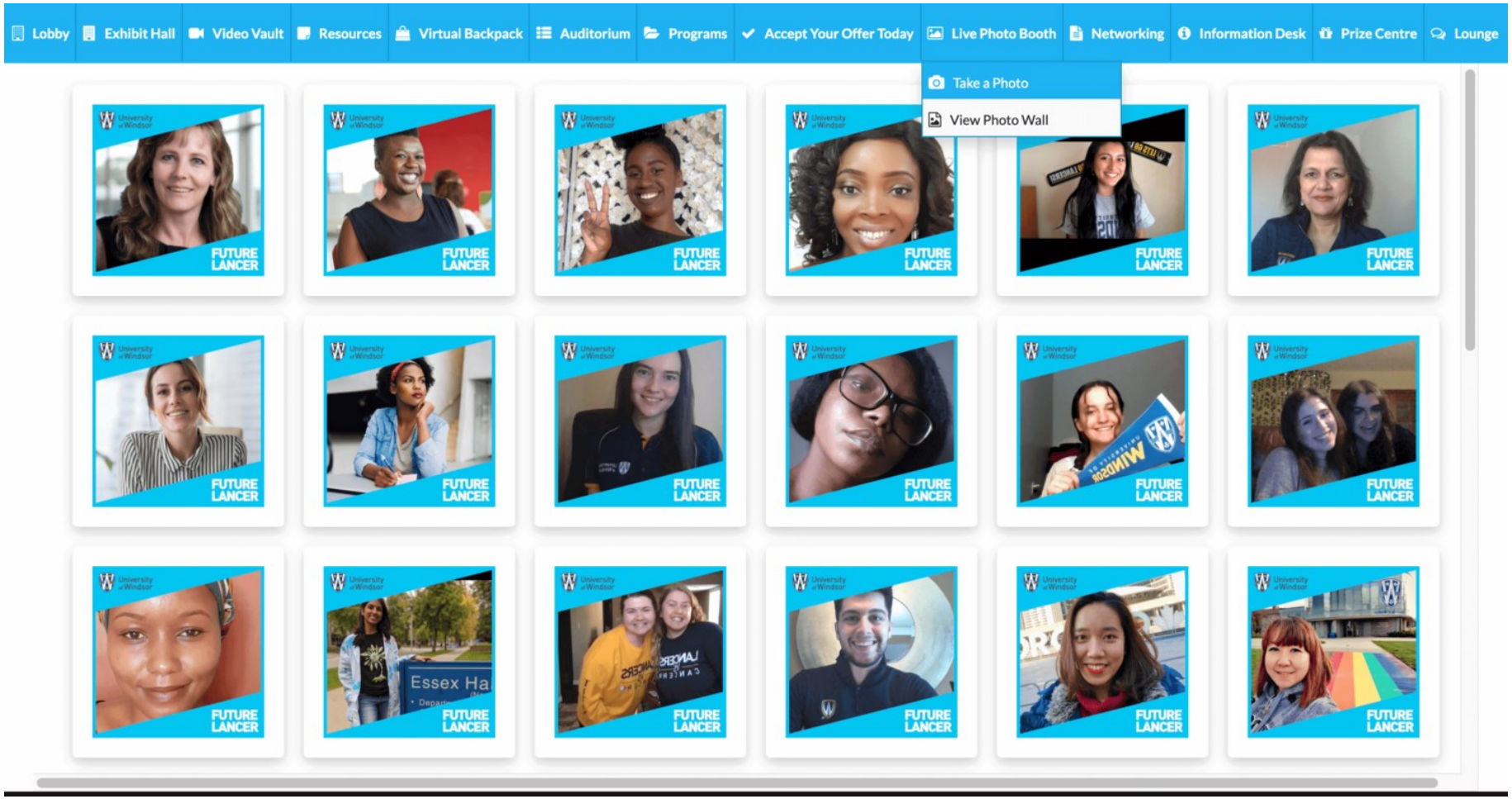
https://en.wikipedia.org/wiki/Hybrid_event

Hybrid Event: Landing Page

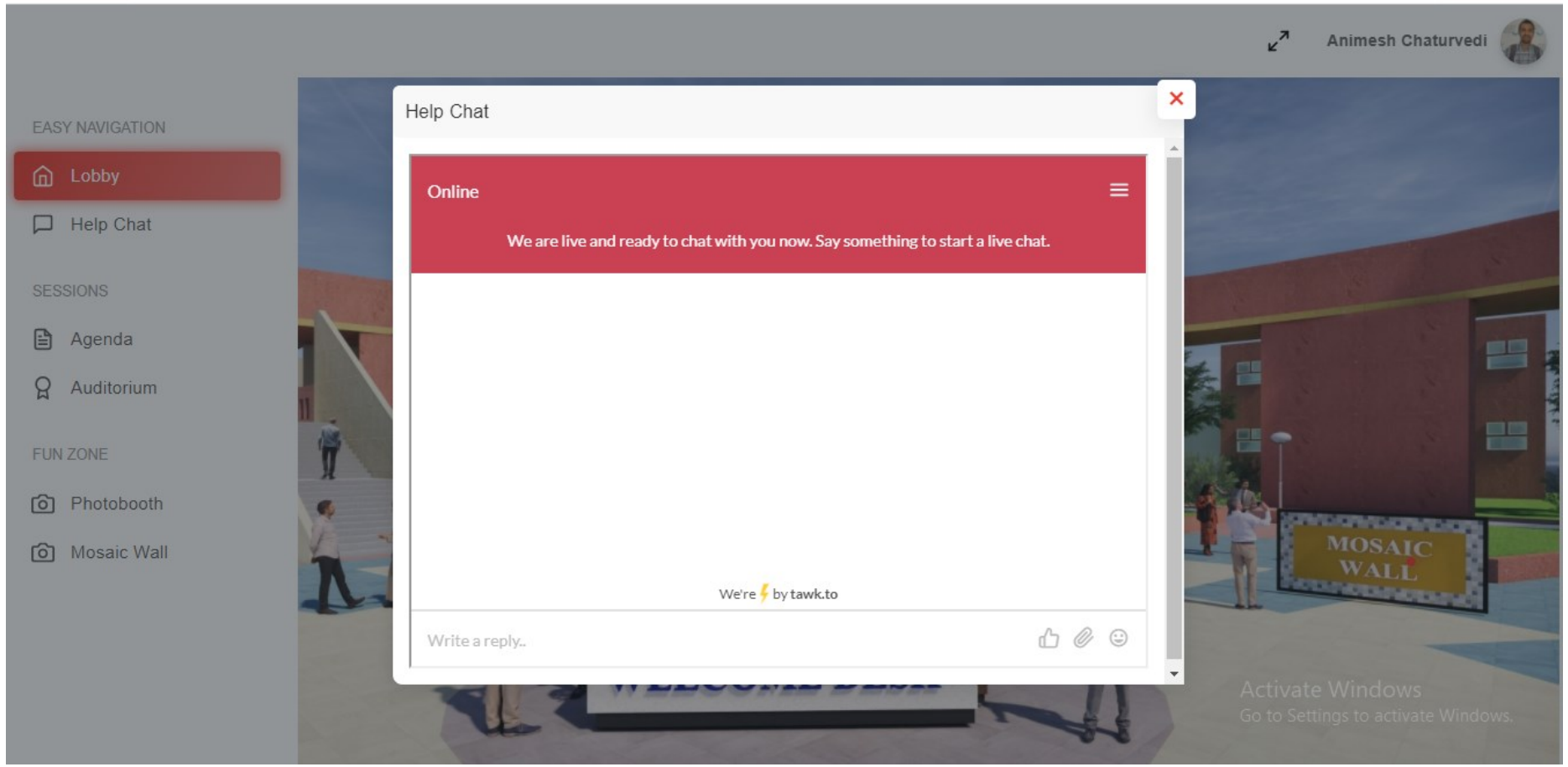
Hybrid Event: Landing Page



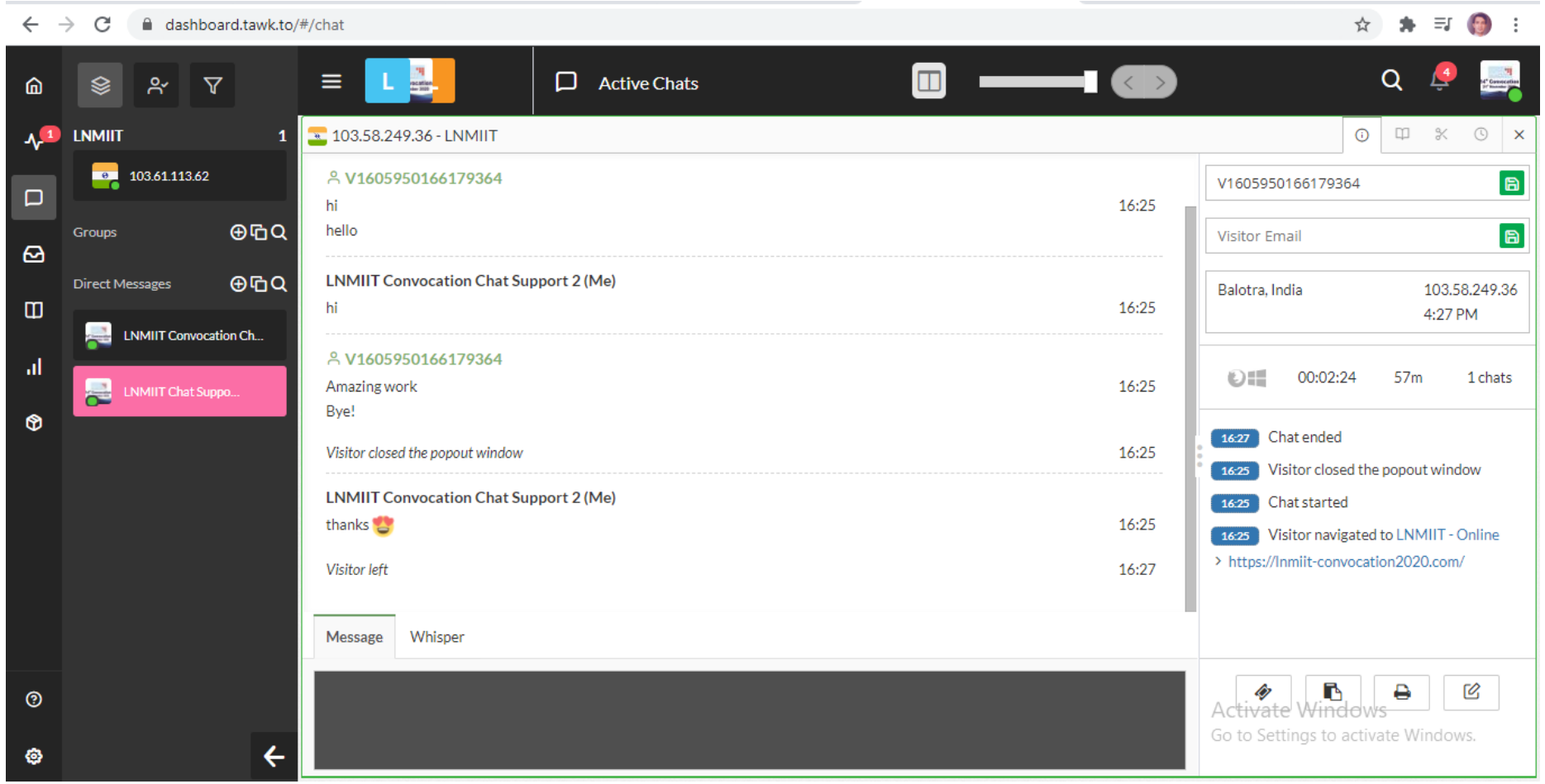
Hybrid Event: PhotoBooth



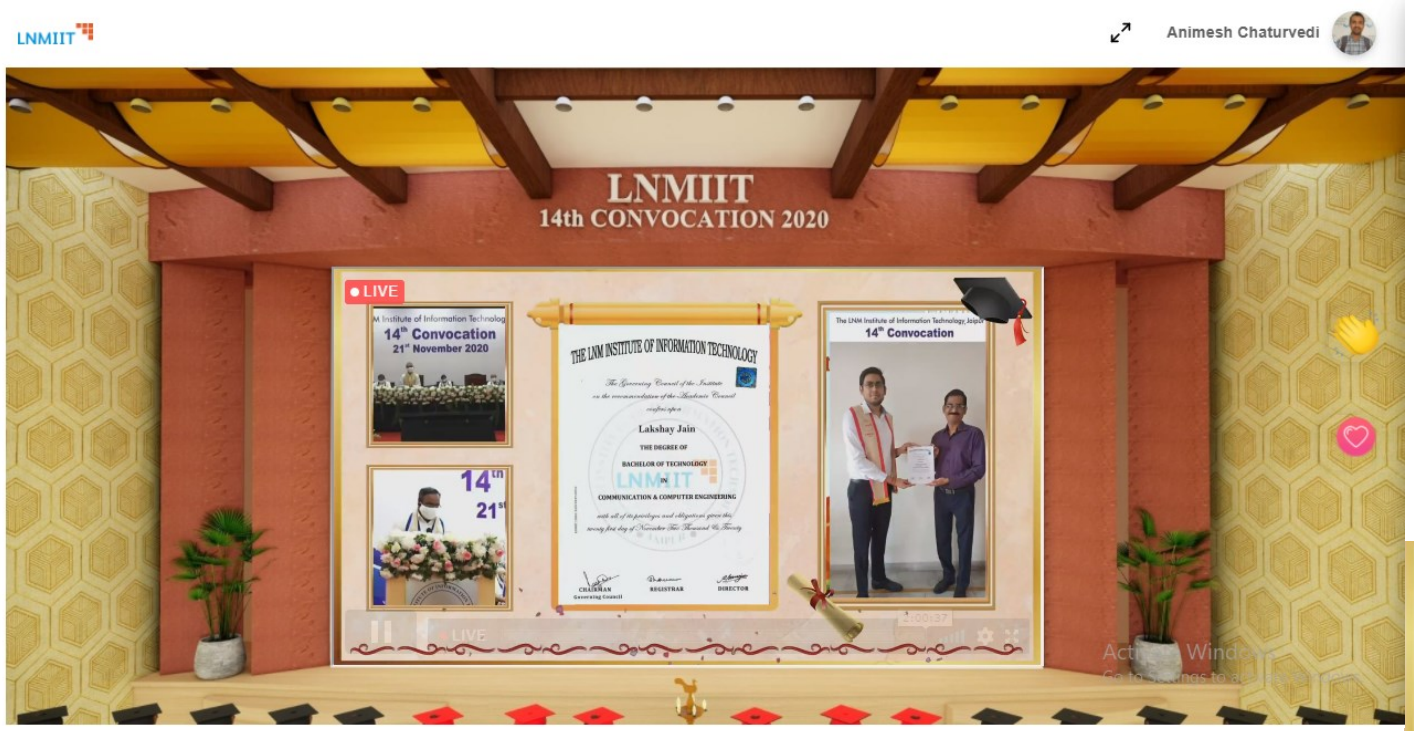
Hybrid Event: Help Chat FrontEnd



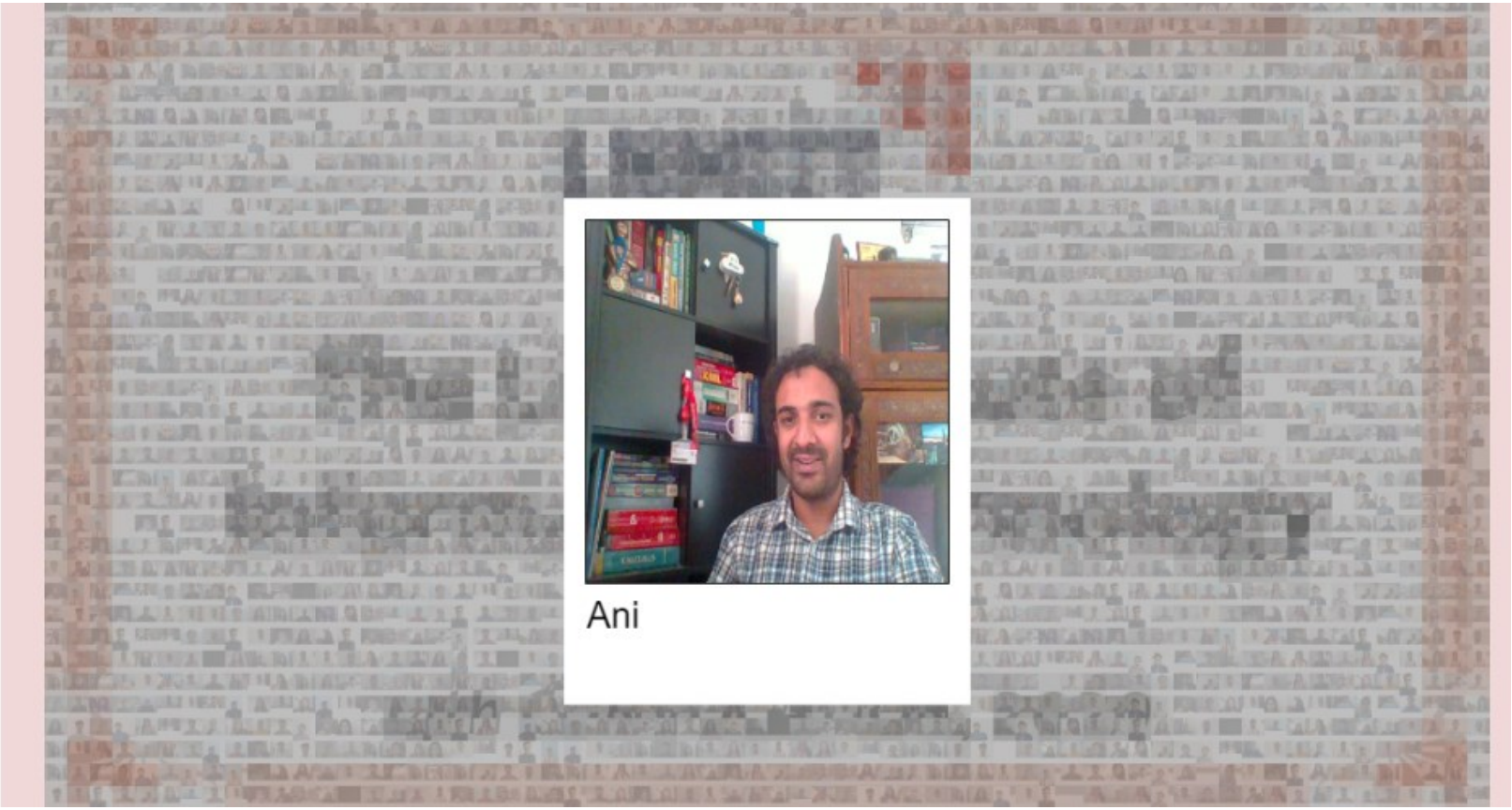
Hybrid Event: Help Chat BackEnd



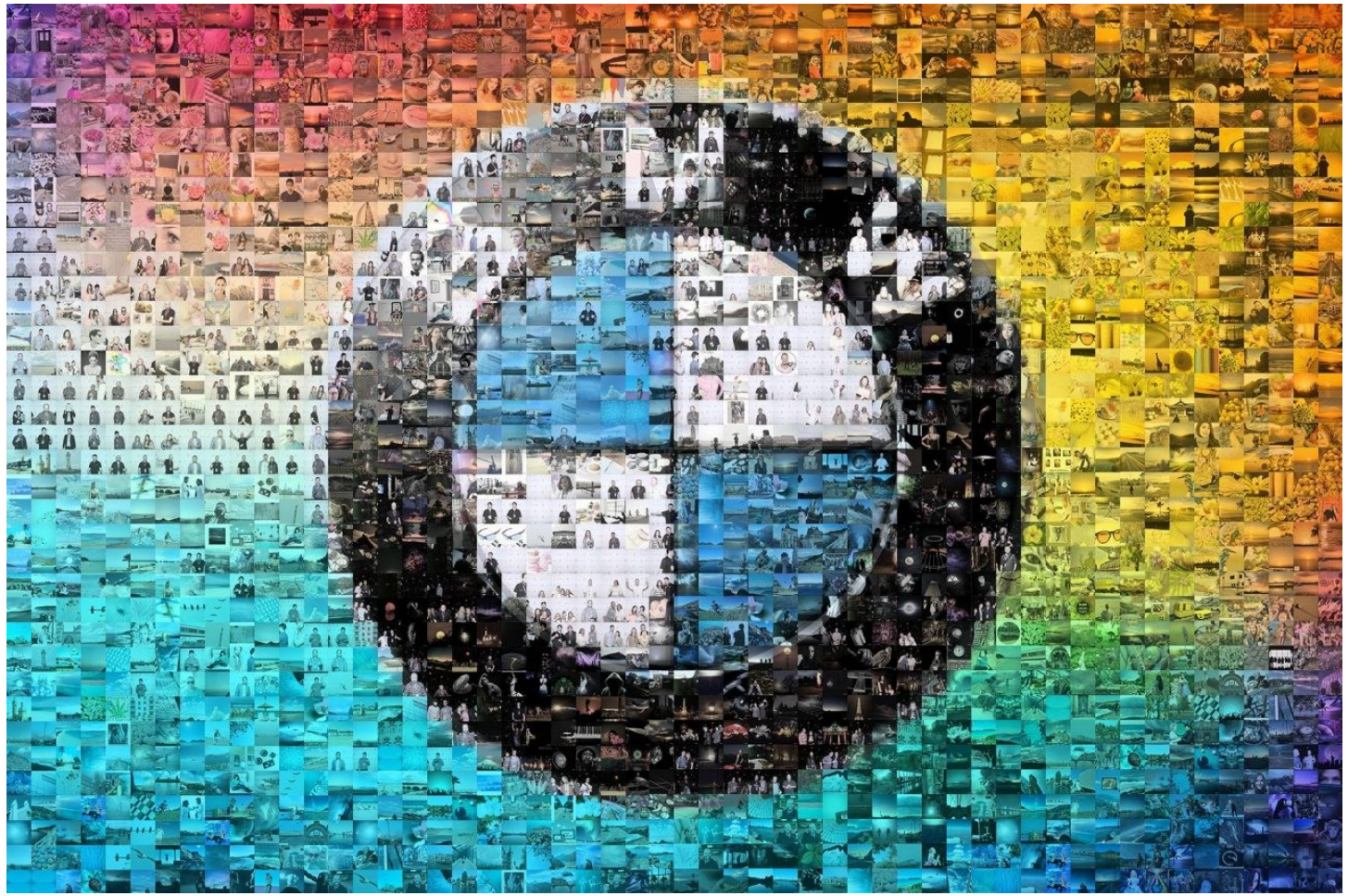
Hybrid Event: Virtual and Physical Degree



Hybrid Event: Mosaic Wall



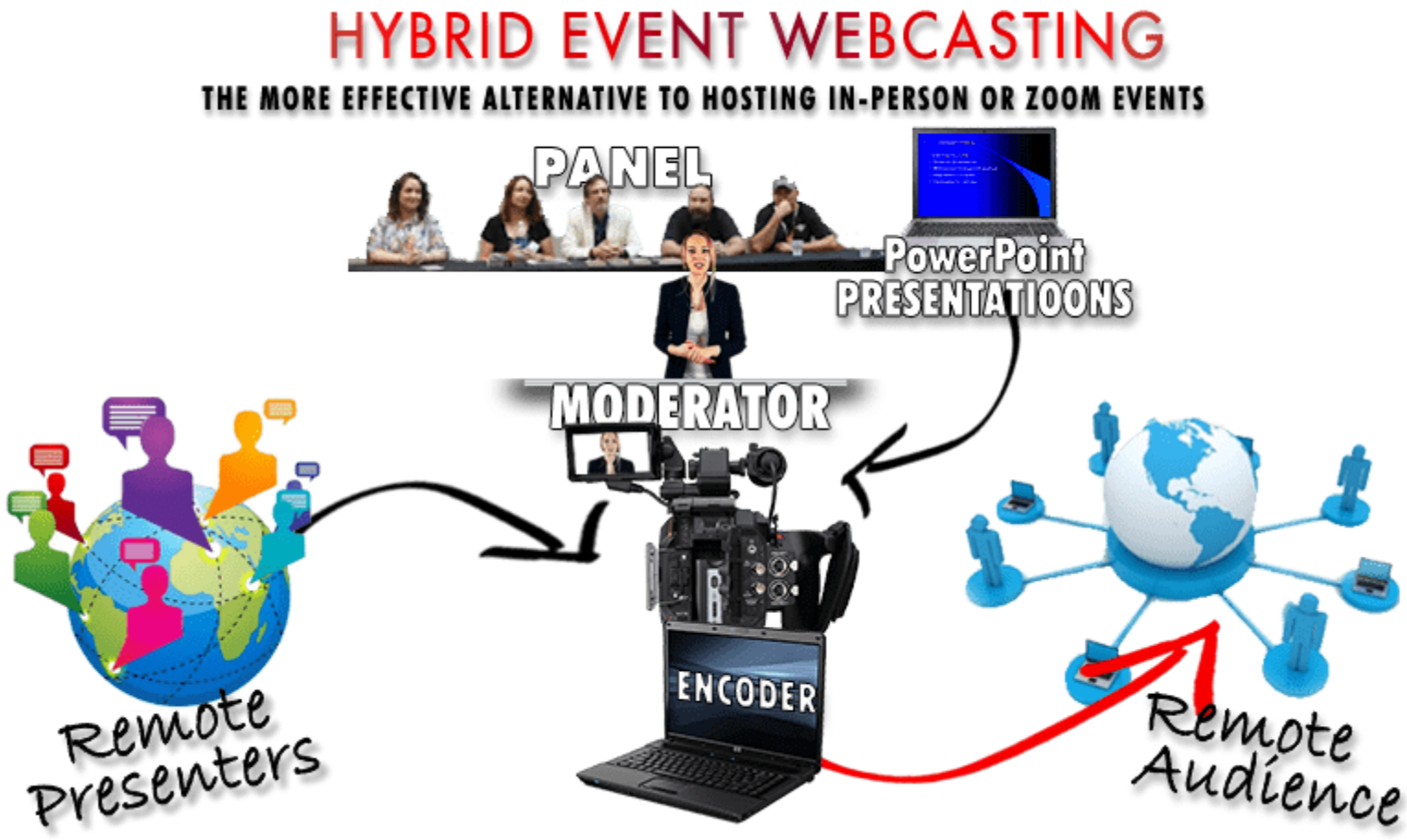
Hybrid Event: Mosaic Wall



https://www.youtube.com/watch?v=BSwJCRKvmPc

Hybrid Event: Blowing Flower Effect

Hybrid Event: Welcome WebCast



Hybrid Event: Virtual Address

Hybrid Event: Remote Connectivity

References

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- https://en.wikipedia.org/wiki/Hybrid_event

ขอบคุณ
Thai

Grazie
Italian

תודה רבה
Hebrew

धन्यवादः
Sanskrit

ಧನ್ಯವಾದಗಳು
Kannada

Ευχαριστώ
Greek

Thank You
English

Gracias
Spanish

Спасибо
Russian

Obrigado
Portuguese

شكراً
Arabic

https://sites.google.com/site/animeshchaturvedi07

Merci
French

多謝
Traditional
Chinese

धन्यवाद
Hindi

Danke
German

多谢
Simplified
Chinese

நன்றி
Tamil
Tamil

ありがとうございました
Japanese

감사합니다
Korean