# Conference Submission

## Architecture Diagram



Figure 1: The proposed video processing framework architecture.

The system architecture shows how Edge Computing (Shi, Cao, Zhang, Li, & Xu, 2016) is adopted at the camera source to pre-process the video stream, in order to minimise the data transferred to the Cloud through Apache Kafka. Once Apache Kafka receives the pre-processed video data, it is processed by Apache Flink to extrapolate more complex data analytics in real-time. This analysis is then written back to Apache Kafka. Apache Spark is then used to provide distributed machine learning on the messages within Apache Kafka in a real-time capacity. The results are once again written back to Apache Kafka. Finally, a process writes all data within Kafka to a data store which can be queried through a web-based user interface.

## System Evaluation

The base framework uses Apache foundation services in order to provided distributed real-time processing, enabling even the largest of clients to make use of the framework.

### Performance

As the systems all communicate through Apache Kafka, this system is critical to the performance of the application. Apache Kafka was chosen due to its high throughput and low latency, along with its reliability (Kreps, Narkhede, & Rao, 2011). Apache Kafka was benchmarked in a moderately powered configuration (Kreps, 2014).

Figure 2: The throughput of Apache Kafka on a moderately powered multi-node cluster.

The throughput of Apache Kafka enables up to 2.5 million messages to be sent from source per second, which enables even the largest video networks to write the result of video processing to Kafka.

With each of these messages, we also are care about the time it takes from producing the messages to processing it. This is known as latency, and is a key requirement for real-time systems. Kafka has extremely low latency (Figure 3), and is therefore suitable for even the fastest real-time systems.

Figure 3: The latency of Apache Kafka from production of a message to consumption of a message.

Alongside Apache Kafka, Apache Flink and Apache Spark are used for distributed processing of messages, and are therefore key technologies within the system. They can be seen to both be able to extremely performant (Chintapalli et al., 2016), however Apache Spark was able to provide a higher throughput of events, with Apache Flink giving a much lower latency on a per record processed event.

### Limitations

The limitation of distributed processing is the network latency of any deployed system, as each node in a cluster must communicate with its counterparts to organise and distribute work. This can drastically reduce the performance of the proposed framework is deployed onto a degraded network environment. However, this is mitigated by the frameworks deployment to Cloud infrastructure, with intense processing happening at the edge of the infrastructure.

## Use Case

The proposed framework provides core video processing functionality that enables extension and flexibility to meet a broad range of client use cases. Presented below is a conceptual use case showing the frameworks successful adoption to a specific domain, providing core insights and analytics into the video footage in real-time.

### Scenario

The Abbey Road in London, pictured on the front of the famous Beetles album “Abbey Road”, is a popular destination for tourists and locals attempting to recreate the album cover for themselves. Due to this, it is under live surveillance by a multitude of video cameras at all times. This presents an opportunity to gain real-time analytics of the activities occurring at the crossing.

To achieve this the proposed framework is deployed to detect cars and people within the live video stream, extrapolate activities to track walking, standing and people attempting to recreate the album cover photo. It will analyse the activity log for anomalies, alerting the users upon discovery an anomalous event.



Figure 3: The famous Beetles cover “Abbey Road” (<https://www.google.co.uk/search?q=beatles+abbey+road&safe=off&rlz=1C5CHFA_enGB750GB750&source=lnms&tbm=isch&sa=X&ved=0ahUKEwi5rJ_ehO_ZAhUMCsAKHTLaA9IQ_AUICigB&biw=1280&bih=612#imgrc=sJtcKFJFhoc5cM:>)

In order to evaluate the proposed frameworks adoption success, we will focus on the performance and extensibility of the framework, showcasing its flexibility to support real-life client domains.

### Implementation

As the proposed architecture diagram shows (Figure 1), client-side processing is enabled in order to maintain real-time requirements and limit the stream of data from the device. This enables the detection and tracking of people and vehicles to occur at or near the device source.

When identifying cars and people within the video feed, the base framework allows the use of Haar Cascades (Viola & Jones, 2001). This is a common, high-performant, detection methodology that provides an acceptable accuracy rate in identifying objects (Figure 4). We have to make no changes to the base framework in order to detect people and cars, which makes the adoption of this package smooth.

Between frames, tracking needs to occur in order to give people and vehicles a persistent identity, enabling the computation of further server-side analytics in identifying object movement patterns. Providing this is a Kernalized Correlation Filters (KCF) tracker (Henriques, Caseiro, Martins, & Batista, 2015), which tracks an object by treating its location as a set of positions (‘bags’) that each could contain the objects location based on its previous location. It looks at overlapping positive regions identified to possibly contain the person or cars location to provide an accurate final decision on the objects location.

The base framework enables video stream processing in the form of a Python application, making use of OpenCV for performant video analysis tools (“OpenCV Library,” 2018). In this case we could deploy the application on a Linux machine, at the edge of the cloud infrastructure, enabling real-time streaming of the live video to occur with low latency.



Figure 4: The deployed video processing framework identifying people and cars within the “Abbey Road” real-time video stream.

Once the video stream processing was deployed and correctly capturing people and cars, the next phase is to allow it to communicate with the other Cloud-based services. This was enabled through a deployed Apache Kafka cluster on Amazon Web Services (AWS). The video stream processing application published messages containing the locations of objects to the cluster which could then be consumed by server-side services.

In order to gain a deeper insight into the video stream, and enable the objective of identifying people performing the “Abbey Road” album cover, an activity analysis service was needed. The base framework uses Apache Flink for this capability, and has built in behaviour for detecting walking, standing and running activities. The framework can then be extended to not only detect people standing, but to identify four people standing, with the correct distribution, that would be considered an impersonation of the album cover. As Apache Flink comes with advanced pattern matching, this is a simple extension to make to the framework. This capability was deployed on a distributed cluster in AWS, enabling a high throughput and low latency identification of activities.

The output of the activity analysis service is the locations of the activities it has identified, which are written to the Apache Kafka Cluster.

With the knowledge of the activities being performed, and their locations, an anomaly detection service can be utilised to identify unusual activities within the video feed, and alert the user when something that deviates from the norm is detected. Providing this service, the base framework makes use of Apache Spark to deploy a distributed K-Means (<http://theory.stanford.edu/~sergei/papers/vldb12-kmpar.pdf>) machine learning model. This service can run on AWS in its own multi-node cluster. The model is fed the normalised activity locations, along with a dimension for the activity type, and is then able to calculate how far an activity deviates from the centre of common activities. This enables the detection of not only activities performed outside of their normal locations within the video stream, but also activities of an unusual type. This gives the service the power to identify the album cover activity as an anomaly if it is not being performed often, however if there is a series of video that has frequent similar activities, the model can adjust itself to detect that as the normal, giving it the ability to adapt to changing behaviours.

The service then outputs the deviation of a given activity from the normal to Apache Kafka, which can then be consumed by a simple service that sends an alert when a deviation above a given threshold is produced.

As the base framework comes with deployment scripts written in Terraform for all the discussed technologies; Apache Flink, Apache Spark, Apache Kafka, the deployment of the entire application to AWS is simple. The scripts require minimum setup, and one click deployments of individual services, meaning we could include new services within the system as and when they are configured.

### Performance

As this is a single camera use case, where we produce a message for each frame containing the objects we are tracking, we only require a throughput of around 10-15 messages per second. As shown in the performance section, the throughput of the technologies chosen within the base framework allow hundreds of thousands of messages to be processed per second. This enables our real-time requirements with no modification to the base framework.

### Conclusion

In conclusion, we can see through this real-world adoption of the proposed base framework that the framework can be adopted with ease to bespoke use cases. Further to this, it is able to meet real-time requirements through its use of distributed technologies, without the adopting user having to deal with complex infrastructure deployments, allowing them to focus on their unique application.

## References

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