

# PERSONALIZED MOOC RECOMMENDATIONS

*MOOCREC V2*

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MOOCs, chosen just for you.

coursera

UDACITY  
Learn. Think. Do.

edX

canvas  
NETWORK

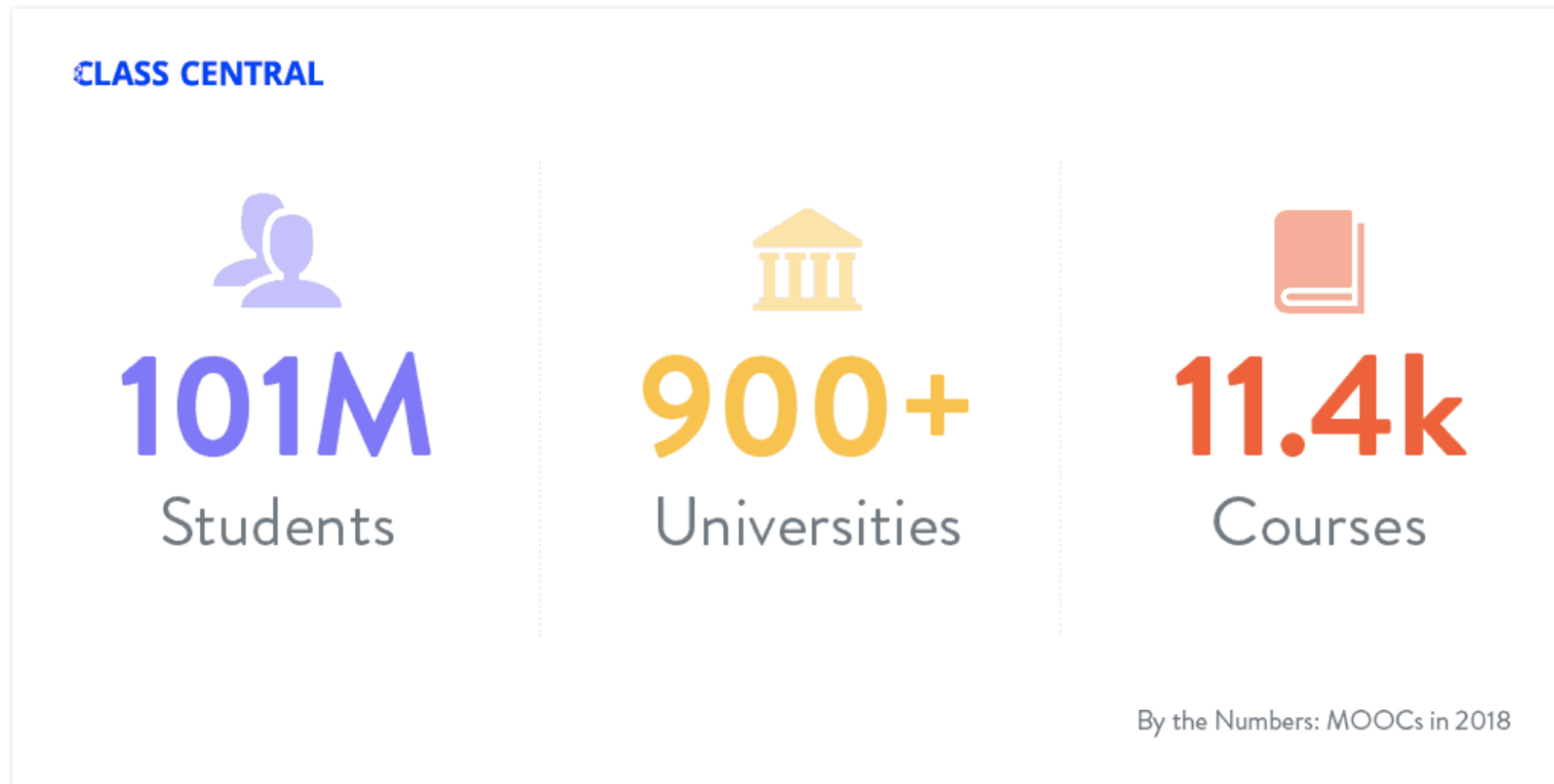
NovoED

iversity

OPEN  
2 STUDY

Future  
Learn

# AN OVERVIEW OF MOOCS



Source:  
<https://www.class-central.com/report/moocs-stats-and-trends-2018/>

Figure 1: MOOCs Statistics from Class Central

# RESEARCH PROBLEM

- ✓ MOOCs have different video production styles
- ✓ MOOCs have a low completion rate
- ✓ Consumers prefer different types of video production styles
- ✓ Lack of connection between MOOC recommenders' and consumers' preference for video production styles
- ✓ No personalization exists for MOOC recommendations

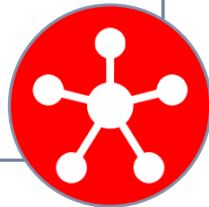
# GENERAL OBJECTIVES

- ✓ Identifying user's learning styles by a more interactive method
- ✓ Implement support for parallel processing to significantly improve performance
- ✓ Improve MOOC recommendations based on information within discussion forums
- ✓ Add support for categorizing newer & more complex video styles

# SPECIFIC OBJECTIVES

- A catalogue of MOOCs from most popular providers
- Forum activity across platforms are analyzed automatically

Hub for  
MOOCs



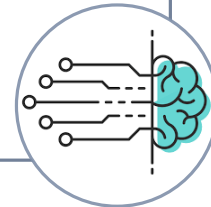
- Identifying user's learning styles by a more interactive method
- Use the sentiments of other users

Personalized  
MOOCs



- Accurately classify a wide range of video production styles
- Efficiently classify using parallel processing

Parallel Image  
Classification



# VIDEO PRODUCTION STYLES

- ✓ MOOCs are delivered in different styles of video
- ✓ Consumers may not prefer some styles of videos
- ✓ Some MOOCs contain multiple video styles

# LEARNING STYLES AND DIMENSIONS

- ✓ People have different styles of learning, according to Felder and Silverman
- ✓ A mismatch between learning styles and video styles exists

# MOOCREC V1

- ✓ A solution proposed by a previous research
- ✓ Proposed solution, MOOCRec V2 extends up on MOOCRec V1
- ✓ Identifies learner styles using a lengthy questioner
- ✓ Covers only a few video production styles
- ✓ Inefficient video classification



# FEATURE COMPARISON

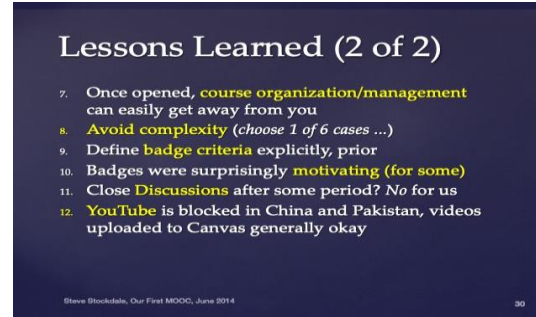
Features	Class Central	My MOOC	MOOCRec	MOOCRec V2 Proposed Solution
Direct learning style identification	X	X	X	✓
Video Production Styles	X	X	✓	✓
Complex and mixed video production styles	X	X	X	✓
Identify the spoken language of the presenter	X	X	X	✓
Search filter based on specific keywords / topics	X	X	✓	✓
User profile and dashboard	X	X	✓	✓
Online discussion forums analysis and extraction of sentiments of forum posts for better MOOC recommendations	X	X	X	✓

# COMPLEX VIDEO PRODUCTION STYLE CLASSIFICATION

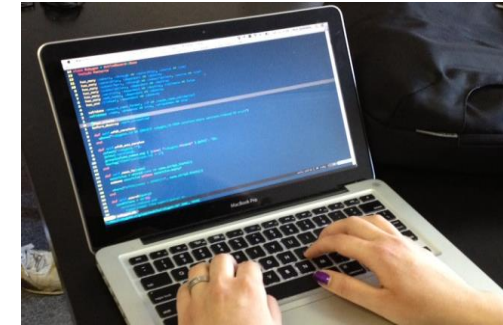
✓ Different types of MOOC video production styles



Talking Head



Presentation slides  
with voiceover



Coding/Demonstration



Conversations



Writing



Animation

# COMPLEX VIDEO PRODUCTION STYLE CLASSIFICATION



Figure 2: Multiple Video styles in one video

- ✓ Some MOOC videos may contain multiple video production styles.
- ✓ Identification of Percentage of each production style in a video.
- ✓ Video will be split into frames and using Convolutional Neural Networks(CNN) frames will be classified.
- ✓ To increase the speed and accuracy of CNN Sparse and Low-rank decomposition shot segmentation method will be used.

# COMPLEX VIDEO PRODUCTION STYLE CLASSIFICATION

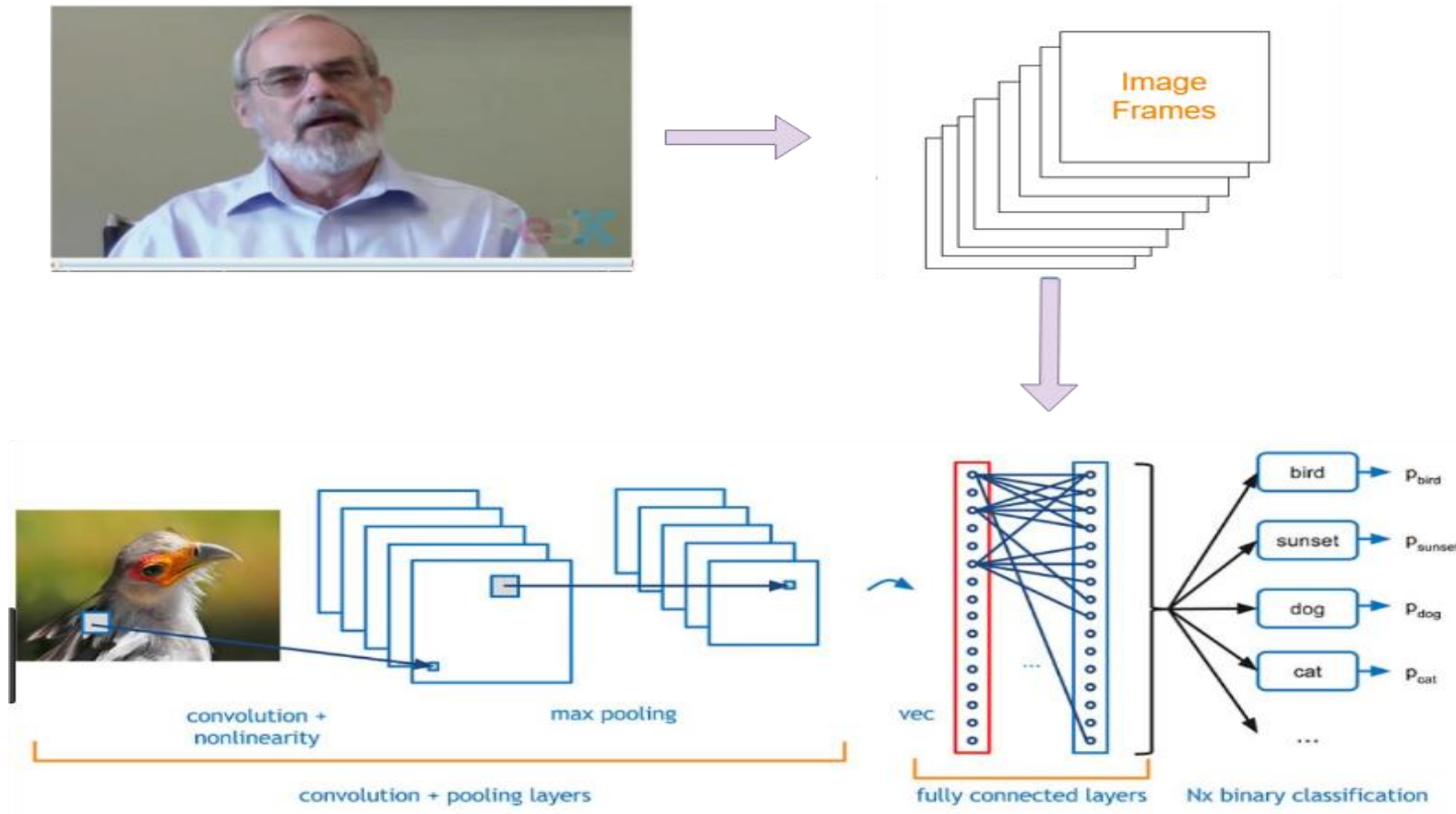


Figure 3 : Video Classification

# IDENTIFYING USER'S PREFERRED LEARNING STYLE

- ✓ Identified using an interactive introductory video
- ✓ Intro video contains MOOCs learning material types recognized by MOOCRec V2
- ✓ Learning material types and [Felder Silverman Learning Style Model](#) are mapped
- ✓ Mapping is introduced based on literature survey

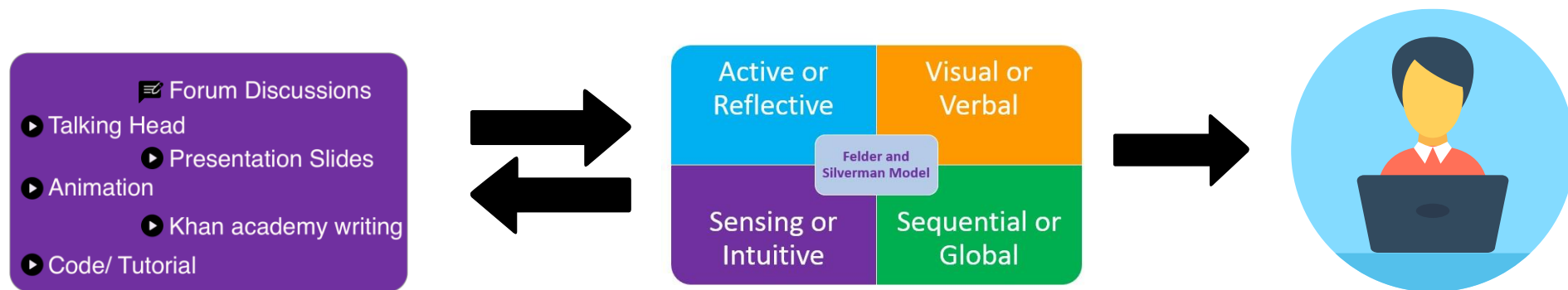


Figure 6: Learning Material Type to FSLSM Mapping

# IDENTIFYING USER'S PREFERRED LEARNING STYLE PROCEDURE

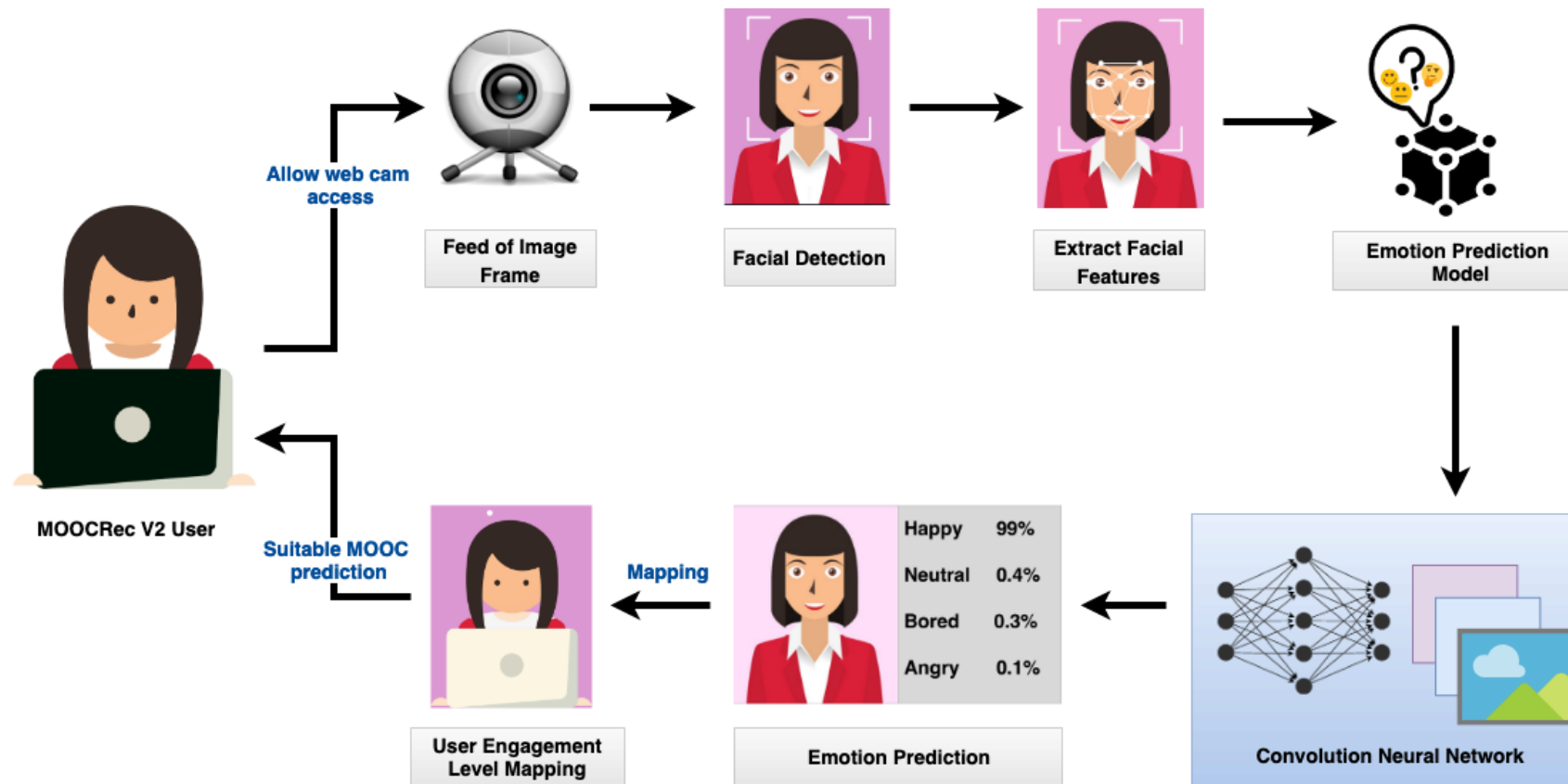


Figure 9 : Procedure of identifying User's Preferred Learning Material

# IDENTIFYING USER'S PREFERRED LEARNING STYLE

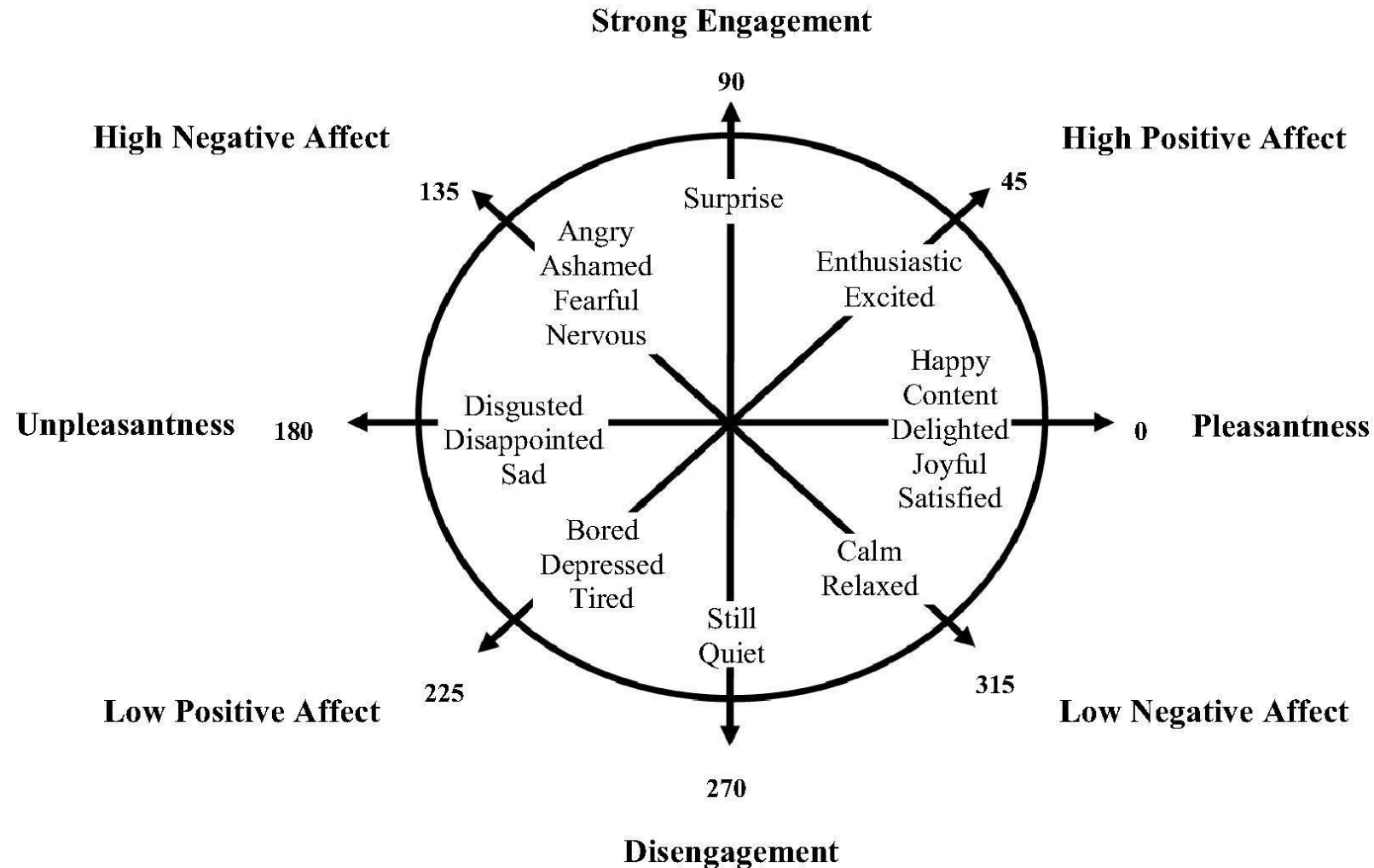


Figure 8 : Academic Emotion and User Engagement Level Mapping

# IDENTIFYING USER'S PREFERRED LEARNING STYLE

## HOW?

- ✓ By identifying user engagement level based on facial emotions
- ✓ Mapped adapting Russell and Feldman model, Watson and Tellegen Model and literature studies

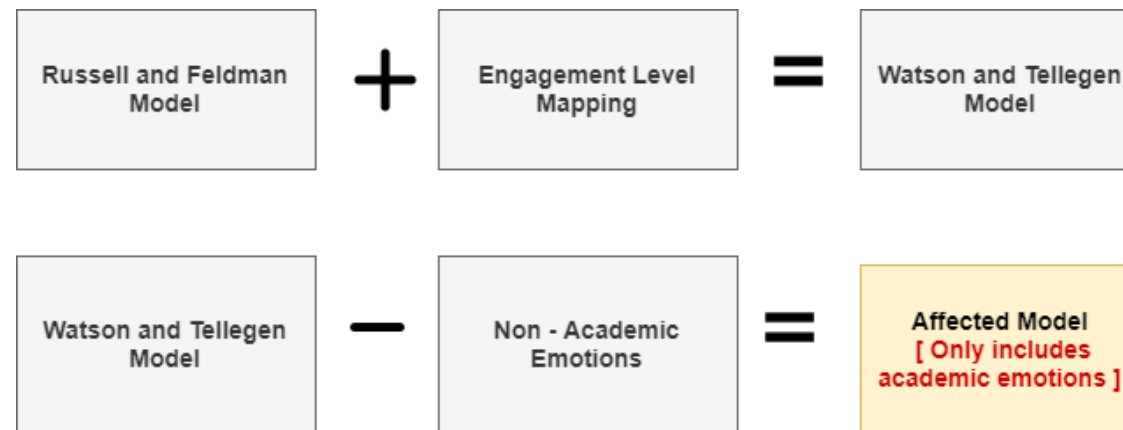


Figure 7 : Procedure of deriving affected model



# IDENTIFYING USER'S PREFERRED LEARNING STYLE SURVEY

Do you like if an online learning platform automatically identifies your learning style or to fill a questionnaire and identify your learning style?

45 responses

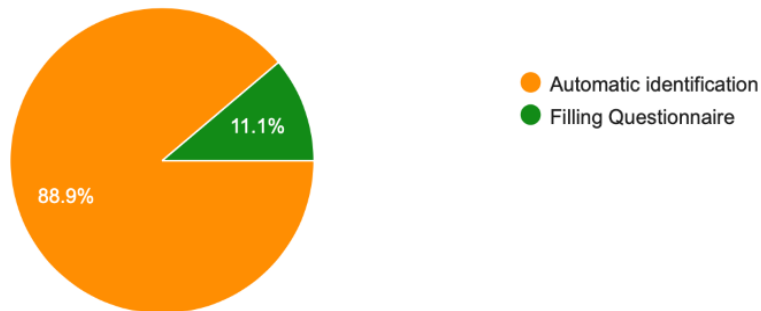


Figure 4 : Survey on Filling a Questionnaire

Do you like allowing the online learning platform to analyze your facial expressions only once by turning on your webcam and watch a video of 5-10 minutes to help you automatically identify your learning style given that your data is not shared with any other party?

40 responses

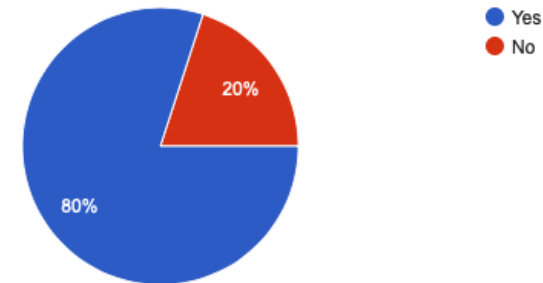


Figure 5: Survey on Users' Willingness to Provide Temporary Web Cam Access

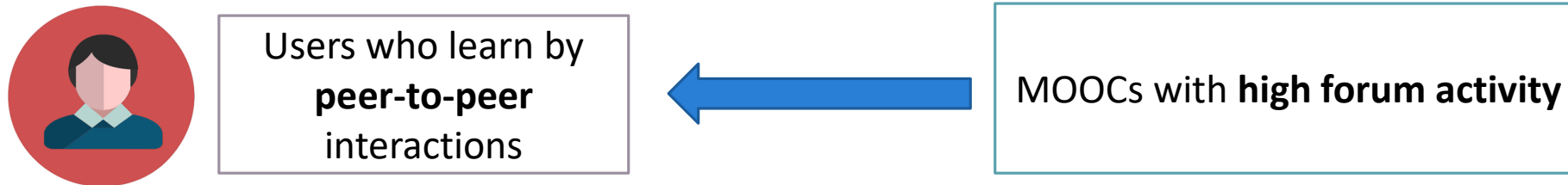
Source:

<https://docs.google.com/forms/d/e/1FAIpQLSfig75HUElsAtCSSNVxGxtzBH7j2jHXakWVn9OvOC-8sjaTgQ/viewform>

# FORUM ANALYSIS

## WHY?

1. Users who prefer learning through peer-to-peer interactions need to be recommended MOOCs which have high forum activity



*Figure 10: Required recommendation characteristic*

2. Currently **ratings & reviews** aren't considered when recommending MOOCs in MOOCRec V1

# FORUM ANALYSIS

## OVERVIEW

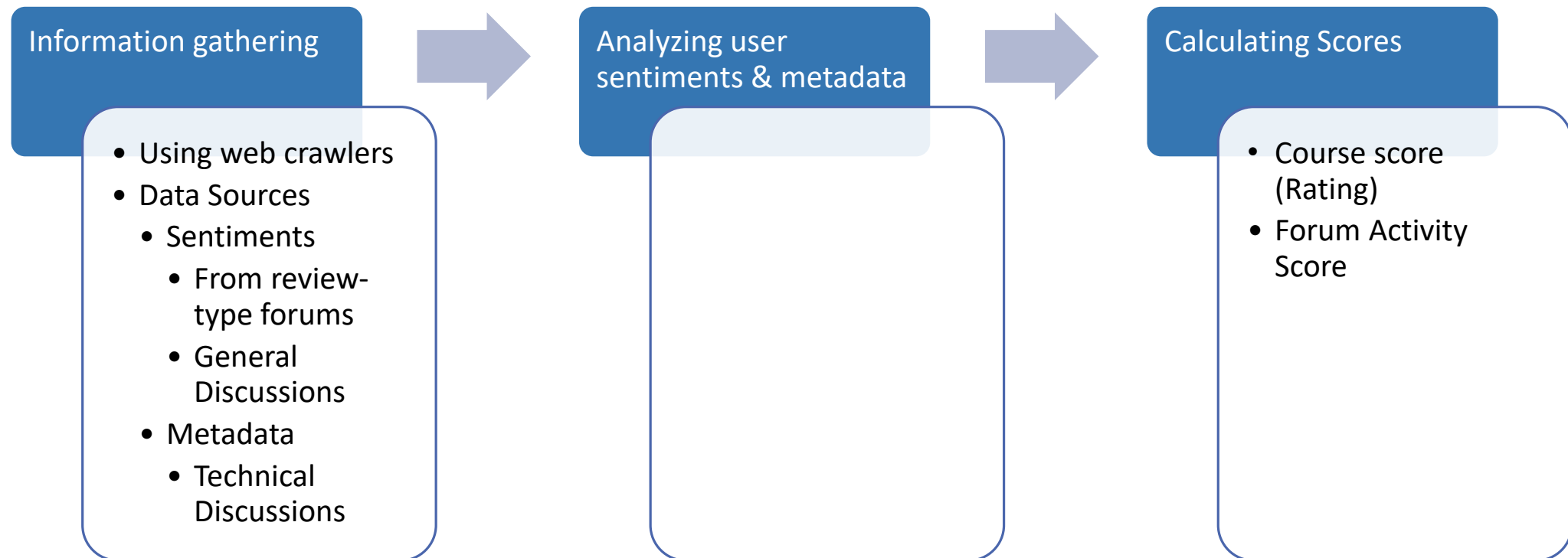


Figure 11 : Forum Analysis Process

# FORUM ANALYSIS

## GATHERING DATA

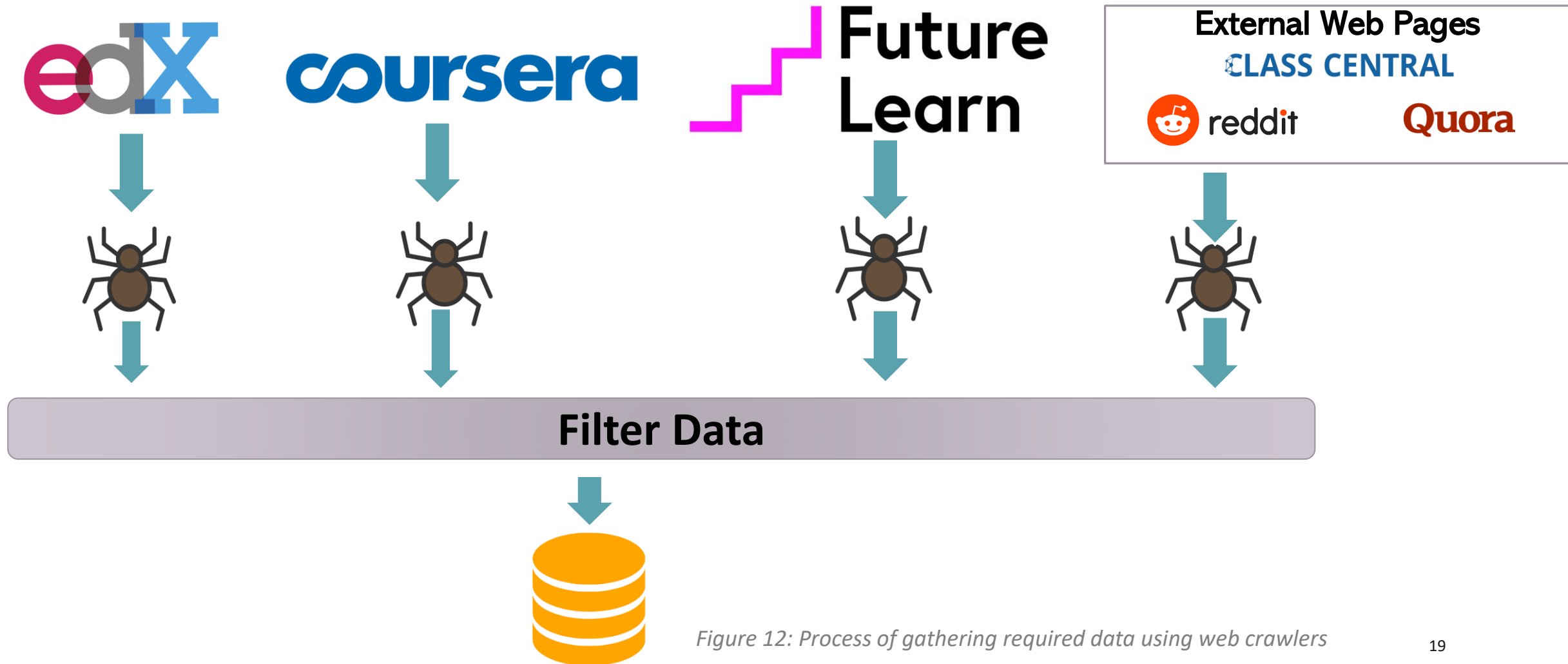


Figure 12: Process of gathering required data using web crawlers

# FORUM ANALYSIS PROCESS

## 1. About the course

- 1. Review-type forums (Sentiment Extraction)
- 2. Ratings from several platforms
- 3. General Discussions



**Course Score**

## 2. Content of the course

- 1. Technical Discussions
- 2. Q & A



**Forum Activity Score**

## 3. About the topic of the course

- 1. Technical discussions about the topic (not linked to a course)



# FORUM ANALYSIS

## EXPECTED RESULT

Course	Course Score (Rating)	Forum Activity Score
Machine Learning – Coursera (Stanford Uni.)	9.2	8.9
Machine Learning – Coursera (Columbia Uni.)	7.8	3.2
Machine Learning - edX	7.6	8.8
Machine Learning – Future Learn	5.4	4.0

# PARALLEL VIDEO CLASSIFICATION

- ✓ Over 11 400 MOOCs right now
- ✓ Assuming every MOOC has one 8-minute video
  - 24 frames per second
  - 480 seconds per MOOC
  - 11 520 frames per MOOC
  - **131 328 000 image frames to Analyze**
- ✓ Analyzing using a single-threaded/monolithic architecture can
  - Cause loss of progress if the classifier crashes
  - Underutilize processing power available
  - Hard to scale to meet increasing/decreasing demands

# PARALLEL VIDEO CLASSIFICATION

- ✓ With parallelized, independent docker containers
  - Workload is distributed
  - Workload is independent
  - No loss of progress by using Message Queues
  - Can scale up or down with ease
- ✓ Ability to run two differently trained classifiers/techniques on the same data set



# PARALLEL VIDEO CLASSIFICATION TECHNIQUES

## ✓ SIMD

- Single Instruction Multiple Data-stream

## ✓ SISD

- Single Instruction Single Data-stream

## ✓ MIMD

- Multiple Instructions Multiple Data-stream

## ✓ MISD

- Multiple Instructions Single Data-stream

# PARALLEL VIDEO CLASSIFICATION

## APPROACH 1

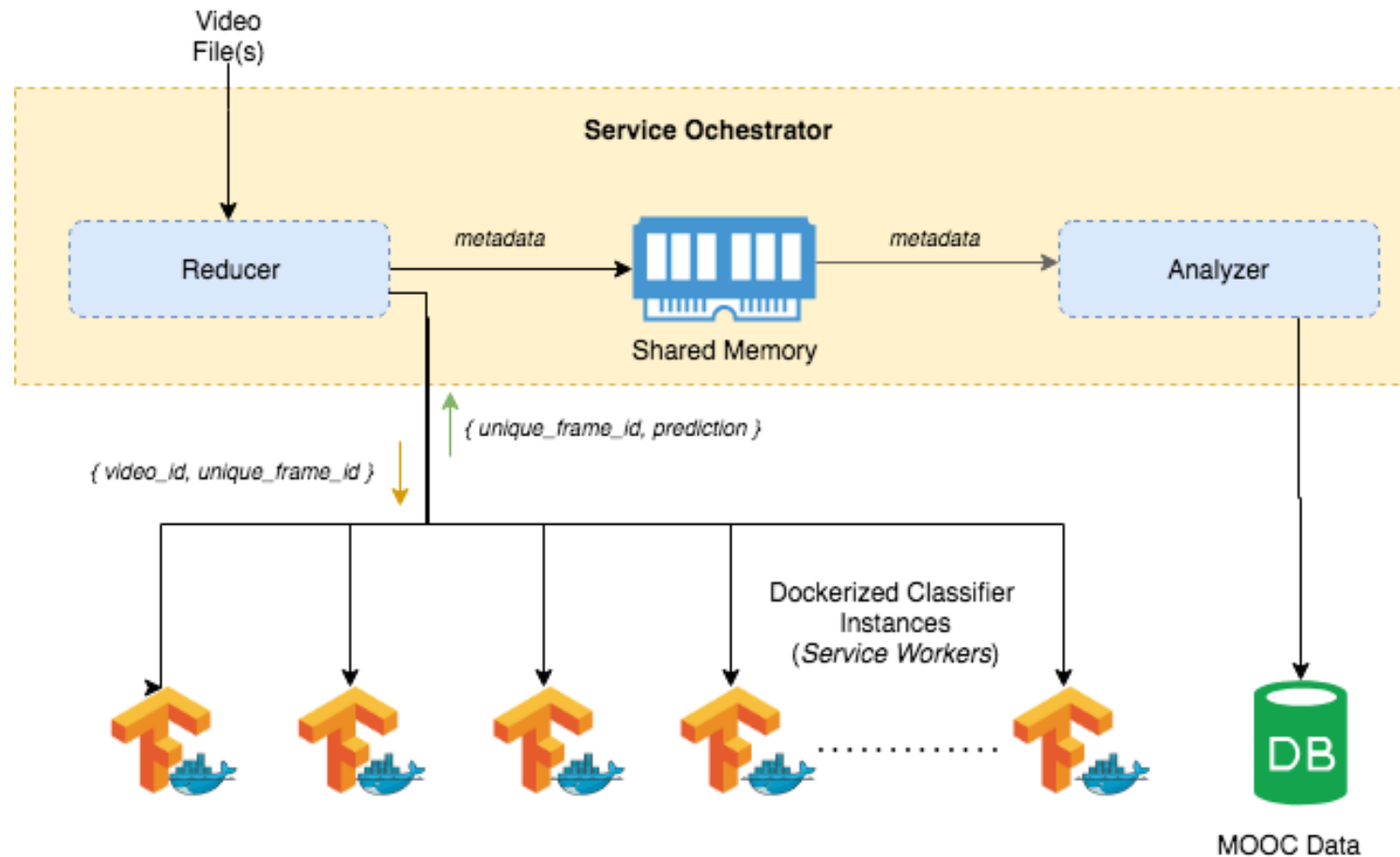
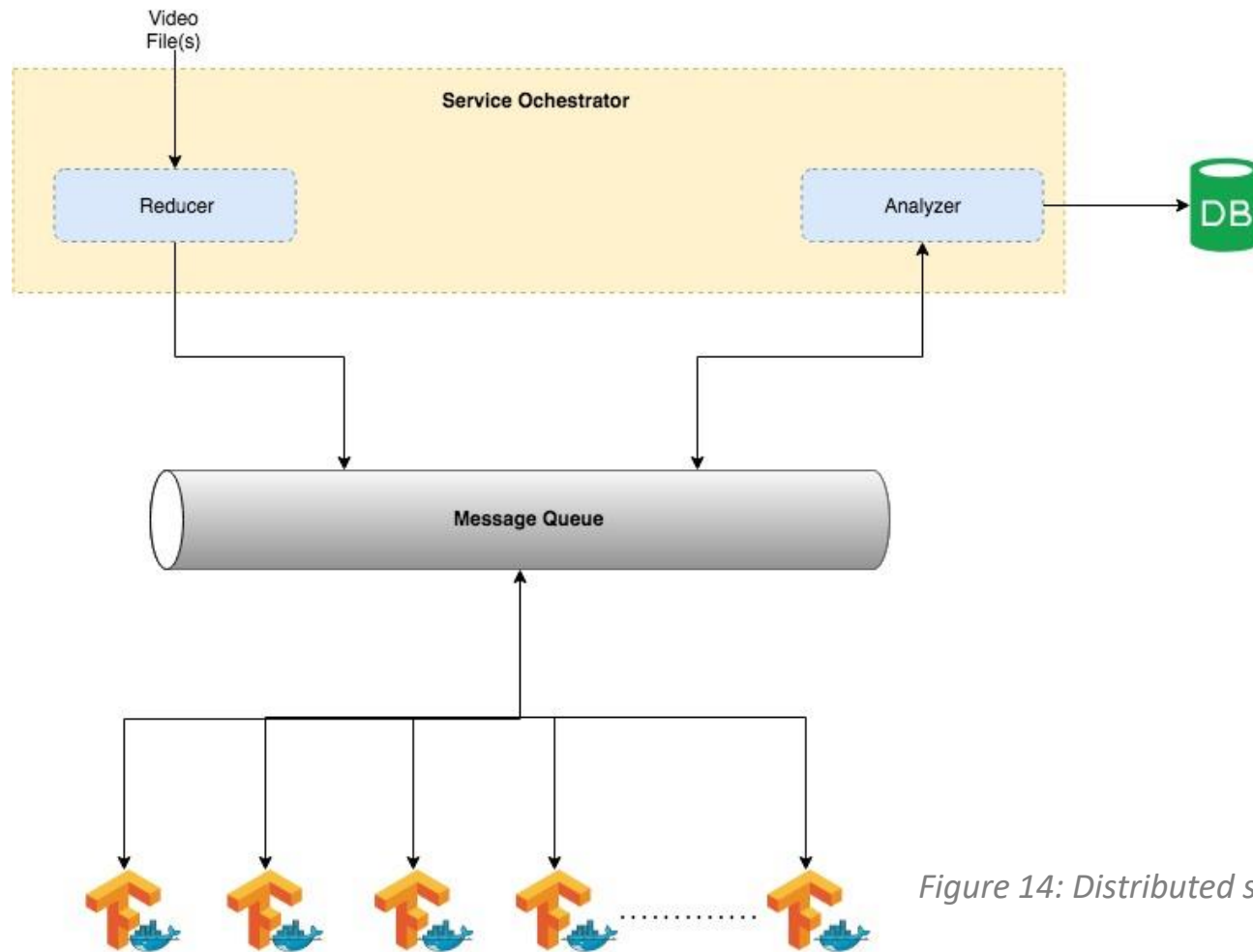


Figure 13: Shared memory orchestrator with distributed service workers

# PARALLEL VIDEO CLASSIFICATION

## APPROACH 2



- ✓ Use a Message Queue to direct work to classifiers
- ✓ Increase scalability
- ✓ Work progress is persistent

Figure 14: Distributed service workers and orchestrator with a message queue

# WORK BREAKDOWN STRUCTURE

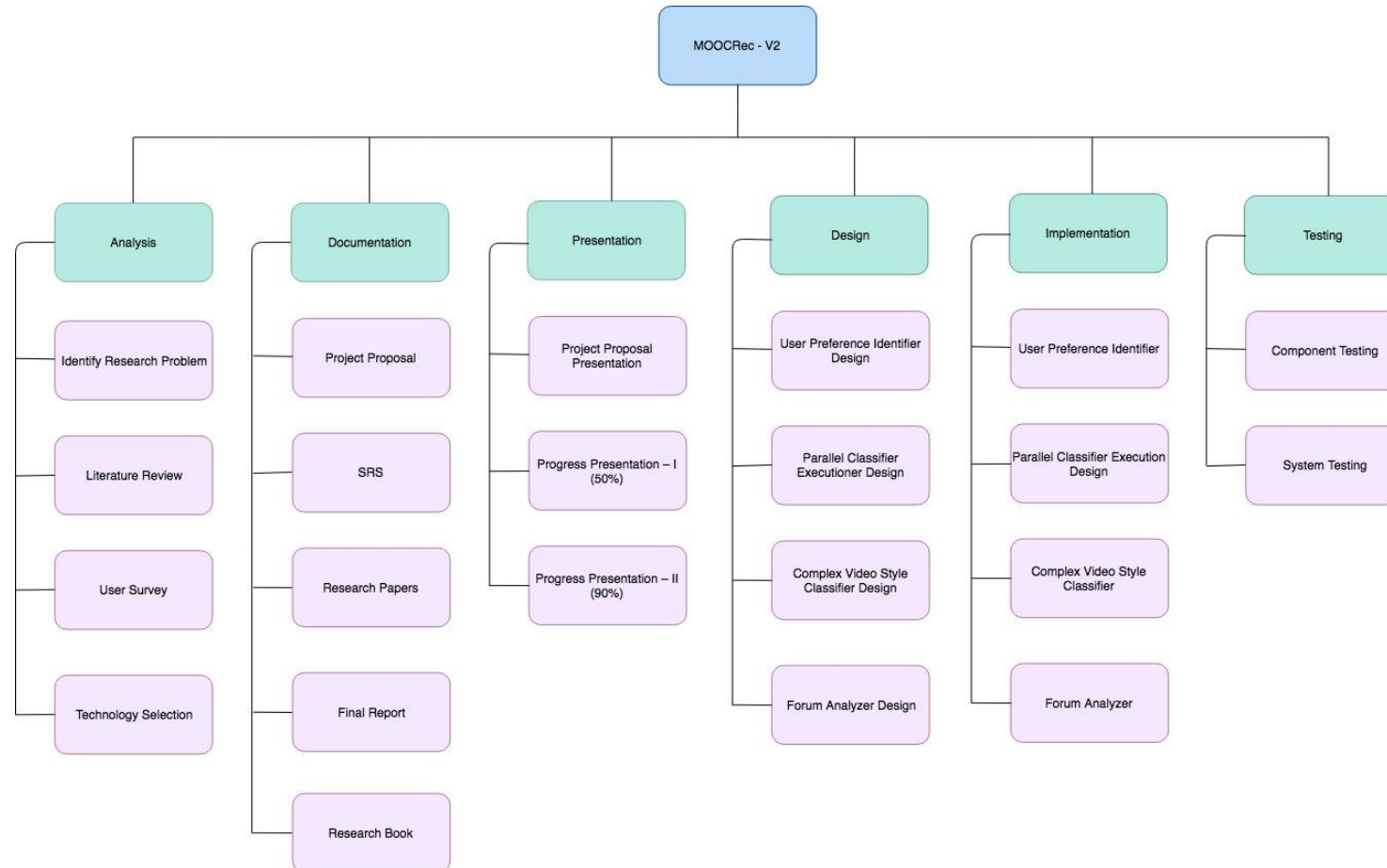


Figure 15: Distributed service workers and orchestrator with a message queue

# GANTT CHART

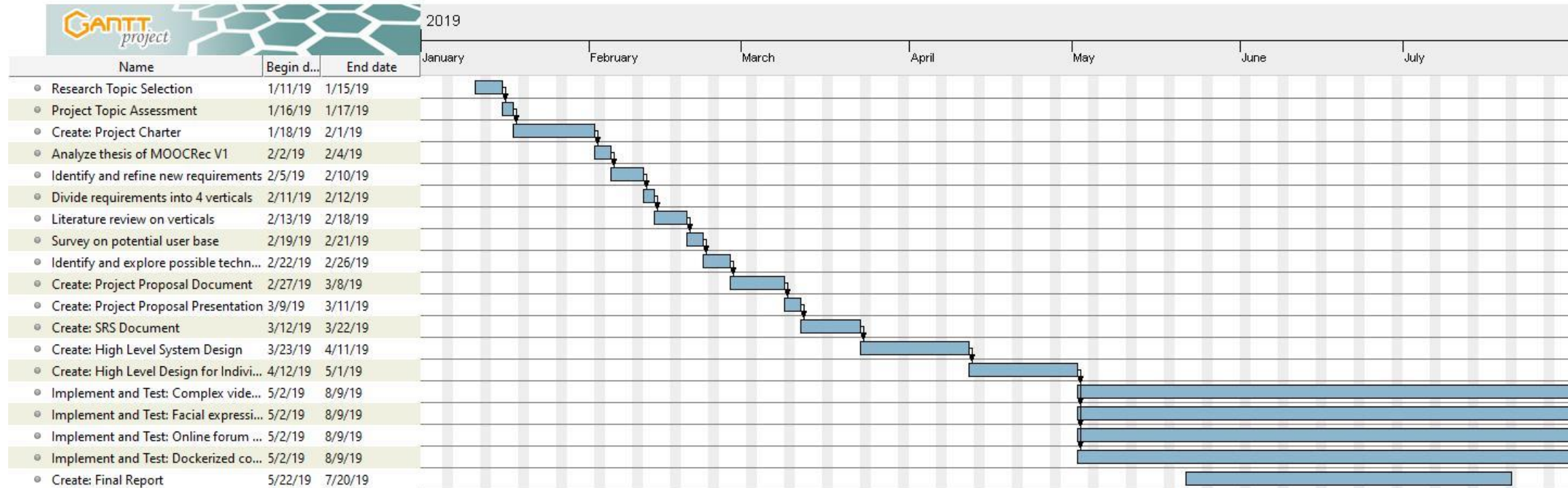


Figure 16: Gantt Chart