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Integration of NLP and Speech-to-text Applications with Chatbots

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Abstract

With the evolving artificial intelligence technology, the chatbots are becoming smarter and faster lately. Chatbots are typically available round the clock providing continuous support and services. A chatbot or a conversational agent is a program or software that can communicate using natural language with humans. The challenge of developing an intelligent chatbot still exists ever since the onset of artificial intelligence. The functionality of chatbots can range from business oriented short conversations to healthcare intervention based longer conversations. However, the primary role that the chatbots have to play is in understanding human utterances in order to respond appropriately. To that end, there is an increased emergence of Natural Language Understanding (NLU) engines by popular cloud service providers. The NLU services identify entities and intents from the user utterances provided as input. Thus, in order to integrate such understanding to a chatbot, this paper presents a study on existing major NLU platforms. Then, we present a case study chatbot integrated with Google DialogFlow and IBM Watson NLU services and discuss their intent recognition performance.

Index Terms – *chatbot, natural language processing, dialog system, apps, deep learning*

Introduction

There has been significant development in Artificial Intelligence (AI) in recent years. While the trend of AI has been there for the past several years [1], it received great attention since AlphaGo [2] won at the Google's DeepMind challenge. Lately, ever since the rise of AI, specifically natural language processing (NLP) and computational linguistics, chatbots are becoming the modern technological aspect in the next generation of conversational services. The chatbots are the human-computer dialog systems that interact with users in a natural language [3]. Digital assistants, intelligent interactive agents, and artificial conversational entities are also known as chatbots. The use of natural language provides offers an intuitive, flexible and easy way in human-machine interaction. Chatbots provide responses or perform actions by processing text or speech, which humans sent digitally and can closely mimic human conversations through NLP techniques and sentiment analysis. The natural language understanding (NLU) engine is the core of a chatbot's NLP task. It is a process of implementing natural user interfaces. NLU allows identifying underlying intents, extract context, meanings and domain-specific entities in users' utterances. The steps that a chatbot takes when specific intents are triggered by user utterances are the actions and these have parameters that mention detailed information about it. Three aspects in a sentence are typically identified by NLU, namely, *intent* that maps users' utterance to a specific class that lets digital virtual assistants to decide a response or action, *entities* that illustrate important information such as date, times and locations, and *contexts* correspond to the context of the object the user is referring to [4]. The accurate response to users' input by a chatbot requires the combination of these intents, entities and contexts.

The tech giants and leading cloud service providers such as Google, Amazon, Microsoft, Facebook, and IBM have been developing cloud-based platforms/ services with NLU engines, AI/ machine learning stack, and necessary development and deployment tools, to enable fast prototyping of digital virtual assistants/ conversational agents. These companies perform computation on their servers, and offer the NLU applications and modules as cloud-based service, on their platform. Some of these services do not require knowledge of NLU algorithms, and hence, are the black-box machine learning models, but expect users to input training examples. In this paper, we perform an in-depth study of the primary NLP applications that are available as cloud-based services, evaluate the performance of a case study chatbot integrated with two of the cloud-based NLU services Google DialogFlow [5] and IBM Watson [6] in a healthcare-based chatbot context. Note that the terms *NLP applications* and *NLU services or engines* are used interchangeably in this study.

The rest of the paper is organized as follows: In State-of-the-Art section, the chatbot types, typical chatbot architecture and major NLP (NLU and Speech-to-text) applications are discussed. NLU Core Features section presents the classification of parameters for the comparison of these applications. In Case Study Chatbot Section, the prototype healthcare-based chatbot created by integrating with two of the NLP applications are discussed. In Experiments and Results Section, the testing is explained followed by the intent classification results of these two platforms. Conclusion Section concludes our study and provides possible future research directions.

State-of-the-Art

Conversational software systems that are designed to mimic communication abilities of humans involving automatic interaction with a user are called chatbots. They are a new, advanced, and modern customer assistance form driven by AI through a chat interface, also known as channel. In this section, we discuss the taxonomy of chatbots, typical chatbot architecture and its constituent components, and major NLU/ speech-to-text applications for integration.

Chatbots Types

The chatbot classifications are done based on the aspects such as the process of response creation, the domain and duration of conversation, and whether they include AI self-learning programs or not. Chatbots are generally classified into two broad groups called task-oriented and conversational non-task-oriented [7]. Task-oriented chatbots assist users to accomplish a particular task and have shorter conversations related to that task. Alexa or Siri helping users in finding nearby restaurants, playing a song, making a phone call or sending text messages are some of such examples. Non-task-oriented chatbots are the conversational ones that engage users in a conversation while answering their questions. These chatbots rely on NLP to extract user information and react with highly matched response and can be setup to either have shorter or longer conversations. More recent works [8] on chatbot implementation have divided chatbots into four groups namely, goal-based, knowledge-based, service-based, and response generated-based. These categories also fall under the former classification of task- and non-task-oriented chatbots. Goal-based chatbots are based on the goal to achieve consist of activity-based, conversational and informative types. Knowledge-based chatbots are based on the knowledge they extract from the data sources or the datasets they are trained on include open- and closed-domain or domain-specific ones. Service-based chatbots are based on the conveniences provided to users including inter-, intra-personal, and inter-agent purposes. Finally, the response generated-based type are based on the process used for response creation and these constitute template-based, generative, retrieval-based, and search engine models, that are further classified based on the different types of neural network and word embedding models [8].

Furthermore, authors in [9] also classified chatbots on an additional aspect related to the permissions provided by the development platform as well as the chatbot component that we prefer to adapt in our use-case. Such platforms fall under two categories namely, open-source such as RASA [10], or closed or proprietary platforms, typically by aforementioned large companies and tech giants that are mostly black boxes and only expose some of the aspects of their implementation in order for us to integrate in our development environment. One major advantages with the services by large companies is the large amount of data that they collect for continuous improvement of their underlying models. In this study, we are interested in the NLU services by these providers or development frameworks. A related work in [11] presents an analysis of three additional widely used chatbot development web platforms called Chatfuel, ManyChat, and It's Alive.

Technical Chatbot Architecture

A chatbot has several major components and a combination/ choice of these components result in an efficient chatbot. Based on the use-case and the chatbot type, the developers choose the algorithms, models, NLP applications, development platform and tools to build it. In fig. 1, we present a generic technical architecture of a chatbot.

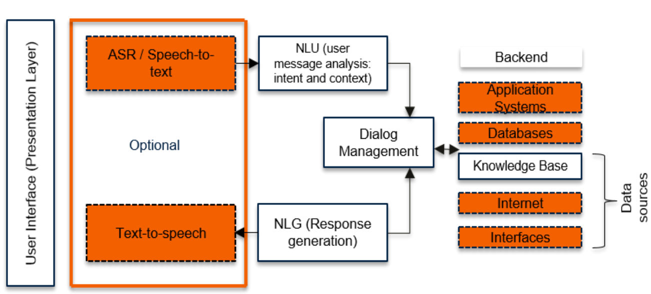

Fig. 1. Generic Chatbot Architecture

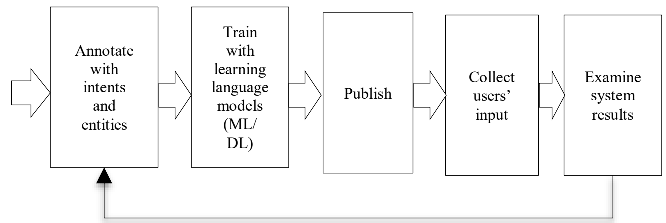

Fig. 2. NLP development process

A generic architecture of a chatbot consists of some mandatory and some optional components. Two types of communication modes as input are possible through the presentation layer constituting of user interface: text or speech. A voice/ speech input needs to be processed to a text understandable by machines using automatic speech recognition (ASR). Next, the language understanding component called NLU parses this text or direct user text input to extract user's intention, context and other annotations such as intent and entities. The dialog management unit performs further processing by evaluating with the backend system and continuously asking for clarification in case it requires more context information. This evaluation is done either through external application systems through API calls or by querying the data sources such as database consisting of user interaction history or knowledge base. The chatbot performs the requested actions based on this evaluation. The result is then converted to a natural language via natural language generation (NLG) unit, that is a response generation component. If needed, the generated text can be sent as audio using text-to-speech component or sent as text typically.

NLU and Speech-to-text Applications

In this study, we focus primarily on the NLU applications that comprise of both text-to-text and speech-to-text based. More specifically, the NLU incorporated in the existing frameworks for developers. To that end, there are several NLU cloud services, that are available for integration into an existing chatbot development environment in order to be able to understand natural language. Some of these modern and famous ones are: Google Dialogflow [5], Facebook Wit.ai [12], Microsoft LUIS [13], Amazon Lex [14], IBM Watson Conversation [6], and SAP Conversation AI [15], among others [9]. One can integrate these services even without having a complete knowledge of NLP and ML. These services map input text or the machine-readable text converted from speech input into semantic slots. Fig. 2 shows a standard process involved in NLP. Initially, the entered data is annotated with intents and entities similar to entering data as part of cloud-based NLU service. The language processing ML/ DL models are trained using the annotated data. The trained model is then published and evaluated with test user utterances. The NLU services discussed in this study continuously evaluate the bot performance and collect user inputs to improve the model. Most of the mentioned cloud NLU services facilitate creation of intents known as user intent category (at the user utterance level), and entities for extracting word-level information (named entity recognition (NER) and slot filling). NLU services also include pre-defined slots that can be used in our implementation for different scenarios. Most of the NLU services have multi-language support. We discuss some of these services next.

1) Google Dialogflow

Dialogflow's NLU service is part of Google cloud platform. It facilitates integration of natural language processing technologies to existing chatbots and enables developers to provide users with conversation interface for both voice (takes care of speech-to-text conversion) and text inputs. Intents, entities, and contexts are the primary elements that enable modeling of chatbot behavior. Additionally, it provides functionality solely for keyword detection too in case the dialog management is taken care by a separate service in our chatbot application. Such feature is possible with webhooks and fulfillment to customize behavior of chatbots. Intents in Dialogflow link user utterances with the chatbot response or action. Contexts enable differentiation of user requests with different meanings. Dialogflow links to the user interface via many channels such as Slack, Facebook Messenger, Skype, Telegram, and Alexa, among others.

2) Microsoft LUIS

Microsoft's language understanding information service (LUIS) is a cloud-based domain-specific NLU service and comes with the Bot framework SDK. An intent is triggered once the user input is matched with the prior knowledge after semantic check. Similar to Dialgflow, LUIS also has entities to extract information. Unlike other NLU services, LUIS facilitates creation of composite entities required for understanding complex information in user utterance. This service does not let developers control the context parameters and does not have diverse set of domains unlike Dialogflow. LUIS, however requires Microsoft Azure subscription but enables seamless integration with Azure Bot service. Voice commands as input are supported in LUIS as well through the speech recognition service. LUIS learns from its usage with active learning technology. Similar to Dialogflow, LUIS can be integrated with multiple communication channels for user input such as Telegram, Twilio, and Skype, among others.

3) Facebook Wit.ai

Wit.ai is NLP API that assists developers in turning both speech and text into actionable data. It is developed primarily to help with voice-to-text input for Facebook Messenger. Wit.ai service improves Facebook's understanding of voice's semantic meaning. It has voice commands API. Wit.ai is free, even for commercial use. Wit.ai builds the behavior of chatbot using stories. Wit.ai learns from the examples related to real life scenarios that constitute the stories. Wit.ai processes the similar examples as user input, extracts entities and applies logic from already learnt examples [16]. Each story has many user intents. The flow of conversation is controlled using branches and represented by these intents, which can be expressed in graph format. Developers can define and use the predefined entities. Similar to Dialogflow, Wit.ai facilitates webhook integration.

4) IBM Watson Conversation

IBM Watson NLU is a rule-based AI native cloud product and a powerful API. It uses deep learning to extract metadata such as keywords, categories, sentiment, emotion, syntax, relations, and entities from text. Watson NLU can be deployed on any cloud or behind the firewall with the text enrichments available out-of-the-box. It has the support for more than 13 languages to analyze our unstructured data. Domain customization is possible and Watson can be trained to understand our use-case domain (healthcare-based chatbots or bots for technical sales department, among others) and is able to extract customized insights with Watson Knowledge Studio (WKS). A custom model with the domain-specific use-case related entities and relations, allows to identify all the occurrences of an entity in users' utterances. WKS uses ground truth to train a model. Model from WKS can then be deployed to our NLU instance within the WKSs user interface. The integration with our chatbot is then possible by making API calls with NLU. Watson speech to text enables better service to users, allowing them to ask questions using natural language, fast-tracking them to the answers, with custom speech-to-text capabilities. This service is driven by ML and has an AI-powered speech recognition and transcription.

5) Amazon Lex

Amazon Lex enables conversational AI for chatbots, is an Amazon web services (AWS) service developed by Amazon. This NLU service can be integrated to any application using voice and text. It provides advanced deep learning functionalities of ASR (speech to text), and NLU for recognizing the intent from users utterances. Lately, the latest deep learning technologies that power Amazon Alexa are available with Lex that enables integration of NLU (comparatively more complex integration as compared to Watson) with our chatbots for accurate natural language conversation. Lex has in-built integration with AWS Lambda and with other services on AWS. Few example phrases need to be inserted, using which Lex builds a complete natural language model with which users can interact with voice or text. Unlike Watson, the dataset preparation is complex, and the mapping between utterances and entities are relatively critical.

NLU Services Core Features

A cloud-based NLU service such as the ones discussed in the previous section provides some advantages over custom-built software. Some of these are as follows: simple user interfaces to create and modify conversation flow or dialog, easy way of accessing data especially for non-technical users, privacy of user data is protected and in a way with the service provider, the system is scalable on demand and with growing needs, and the easy usability and reusability. The ease of use and reuse is related to the fact that the implementation can be adaptable for other use-cases and can be redeployed for future needs. In this section, we adapt the taxonomy discussed in [17] for evaluating the cloud-based NLU applications and later integrating with our healthcare chatbot enabling faster prototyping without sacrificing the chatbot's intent recognition performance. The core features on which the discussed NLU applications are compared are as follows:

1. ***Usability:*** Relates to the ease of use of the interface provided by the NLU application. High indicates simple and intuitive interface. Medium corresponds to relative difficulty in usage. High relates to difficulty in usage without documentation or user guide.
2. ***Pre-build Intents:*** The number of pre-build or inbuilt keyword groups that the NLU platform offers.
3. ***Prebuild-Entities:*** The number of pre-build entities that the NLU platform provides.
4. ***Default Fallback Intent:*** The fallback mechanism is required if the recognized intent is not present as existing pre-build or defined intent. This feature indicates whether the NLU

platform has the fallback mechanism for intents. Without this mechanism, every user utterance will correspond to a defined intent.

5. ***Automatic Context:*** Indicates whether the platform has the functionality to manage the context of conversation automatically or developers have to explicitly define it at their end of implementation
6. ***Modality:*** It is the conversation flow composition mode adopted by the platform such as form-based or block-based.
7. ***SDK/ Webhook Availability:*** Indicates the existence of toolkits associated with the NLU platform that allows developers to integrate their chatbots with the platform or external software.
8. ***Channel Integration:*** Lists the third-party integrations available with the service.

Thus, considering the functionalities and ease of integration from the aforementioned NLU services discussion, in the current study, we compare our case study chatbot with the intent classification algorithms from Google Dialogflow and IBM Watson Conversation. We focus on English language-based chatbot.

Experiments and Results

For the performance evaluation of the NLU applications, we chose Google Dialogflow NLU and IBM Watson Conversation, both of which have speech and text inputs and relevant post processing before passing to NLU for recognition of user utterances. Based on our case study, which is discussed next, we chose these NLU services primarily because of the availability of webhook/ SDK, high usability and automatic context management. In this study, through the evaluation, we are interested in knowing how accurately the NLU application identifies the intent for a particular user utterance/ sentence and the entities in the sentences. Furthermore, the identified intent is the keyword for the case study chatbot that in turn triggers relevant action and response to the user.

Case Study: SymptomAssistance Chatbot

This section presents our case study healthcare chatbot for smoking related Symptom Assistance for the evaluation of performance of the cloud-based NLU services (Google Dialogflow and IBM Watson Conversation) integration. The original version of the chatbot has SMS and Facebook Messenger integration for user input but rule-based predefined set of responses for user's input. Users of the chatbot were typically aware of the sequence of steps to follow. However, with the increasing complexity and functionality extension of this interactive messaging along with users repeated entry of free text, the longer conversations have been becoming tedious to handle at the backend. Thus, the necessity of integrating NLP applications arose. The readers are directed to [18] [19] for background and details about the smoking cessation chatbot. In the current study, we adapted a small part of the protocol from [18] [19] interventions in order to show the feasibility of off-the-shelf NLU services integration, and assess the performance of two of these services that closely suit our development needs in humanizing the chatbot for more engaging conversation with participants.

Data Description

We created four intents on both the Dialogflow and Watson NLU services: *DiseaseIntensity, Span, TobaccoCraving, and TobaccoCraving-medicine.* Further, we also enabled default fallback intent in these two applications. Fig. 3 shows the list of intents in the SymptomAssistance chatbot. For each of the NLU services, we trained with 10-15 sentences in each intent.

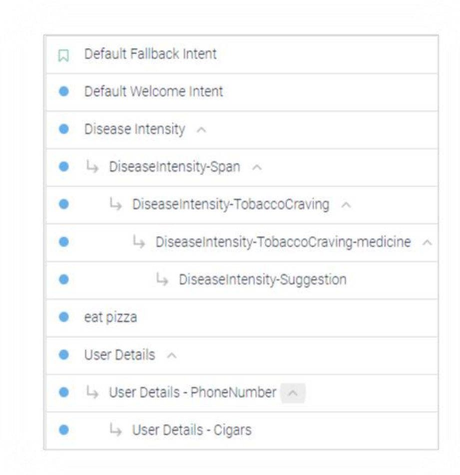

Fig. 3. Intents in the NLU services

Intents are the verbs corresponding to the activities that the user needs to do. Since we want to capture a request and perform an action, intents need to be defined. Entities are the nouns or the content for the action that needs to be performed. Fig. 4 shows an example NLU slot filling and intent parsing tree. Additionally, fig. 5 shows an annotation example of entities for a sample sentence in the current use-case. For every training sentence entered for intent, specific entities and their requirement is highlighted in the NLU service. We also utilized pre-build intents and entities for initial conversation initiation where users enter their phone numbers.

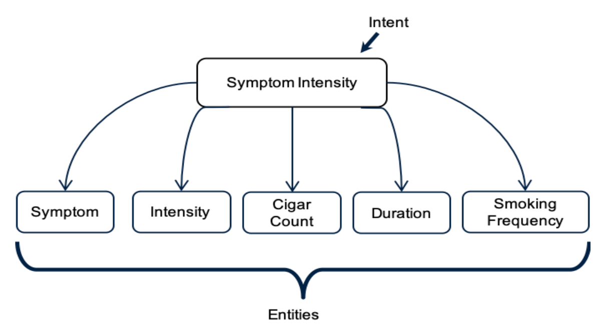

Fig. 4. NLU slot filling and Intent parsing tree

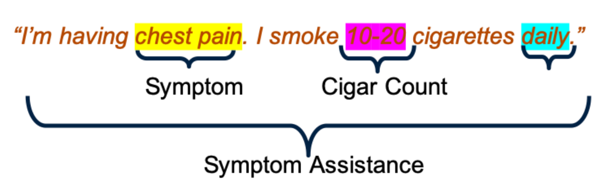

Fig. 5. Intents and Entities Annotation

Results

The NLU applications mostly differ in handling automatic context, default fallback intent, pre-defined intents and entities, and the availability of SDK/ webhook. The details of core features on which we analyzed the five NLU applications in the current study are as follows:

1. Google Dialogflow has high usability. It has 34 and 60 pre-build intents and entities respectively ranging from addresses to colors. It has a default fallback intent and can handle automatic context. It employs form-based conversation composition mode. The online integration is possible with 14 channels ranging from Telegram to Alexa. Webhook and SDK are available for faster prototyping and integration with external software applications.
2. Microsoft LUIS has medium usability. It has 20 and 13 pre-build intents and entities respectively ranging from numbers to geography. It has a default fallback intent but cannot handle automatic context. It employs form-based conversation composition mode. Webhook and SDK are available for faster prototyping and integration with external software applications. From SDK v4, it is possible to integrate the bot created with Azure Bot Service to standard channels such as Alexa, Facebook messenger, and Slack, among others.
3. Facebook Wit.ai has high usability. It has 41 and 22 pre-build intents and entities respectively ranging from location to email. It does not have a default fallback intent and cannot handle automatic context. It employs form-based conversation composition mode. The online integration is possible with only FB messenger currently. Webhook and SDK are available for faster prototyping and integration. It has 5 pre-build traits corresponding to sentiments, greetings, etc.
4. Watson has high usability. It has lately added a lot of pre-build intents that focus on customer care, industry, etc. and has 7 entities respectively ranging from time to person. It has a default fallback intent and can handle automatic context. It employs both form- and block-based conversation composition modes. The online integration is possible with channels ranging from Slack to Facebook Messenger. Webhook and SDK are available for faster prototyping and integration with external software applications.
5. Amazon Lex has a relatively low usability. It has 15 and 93 pre-build intents and entities respectively through Alexa. It has a fallback intent and can handle automatic context. It employs form-based conversation composition mode. The online integration is possible with channels such as Facebook Messenger, slack, and Twilio SMS. Webhook and SDK are available for faster prototyping and integration with external software applications.

Additionally, we also evaluated Google Dialogflow and IBM Watson Conversation NLU applications with four test user utterances and calculated the confidence levels as a metric for accuracy of right intent detection by the intent classification algorithms in the discussed NLU applications. Table 1 shows the results of evaluation on the four composite sentences with the recognized intent and confidence levels for the two NLU applications.

Table 1: Classified Intents with their confidence scores

Test User Utterances	Google Dialogflow	IBM Watson
I am having headache but I never smoke.	*DiseaseIntensity* – 1.0	*DiseaseIntensity* – 1.0
I am suffering from chest pain for the past 2 weeks. I have been smoking for last 10 years.	*DiseaseIntensity* - 1.0, *Span* - 0.99, *TobaccoCraving* -1.0	*DiseaseIntensity* - 1.0, *Span* - 0.85, *TobaccoCraving* - 0.99
I am looking for a treatment for heart burn.	*DiseaseIntensity* - 1.0,*TobaccoCraving-medicine* - 0.92	*DiseaseIntensity* - 1.0
What causes chest pain?	*DiseaseIntensity* - 0.99	*DiseaseIntensity* - 0.88

Overall, the two NLU services perform decently well for the test user utterances. For the first sentence, both the applications detected the correct intent successfully with highest accuracy of 1.0. For complex sentences, such as second, third and fourth in the table, Dialogflow detects all the associated intents more accurately as compared to Watson. The creation of composite entities is found to be more accurate in Dialogflow intention detection algorithm.

Conclusion and Future work

In this paper, we compared the major cloud-based general-purpose NLU applications based on the eight core features for faster prototyping of natural language chatbots. Based on these features, we found Google Dialogflow and IBM Watson Conversation platforms best suitable for integration with our case study symptom assistance chatbot for smoking cessation. Google Dialogflow performs better in recognizing all the associated intents for complex sentences. The discussed NLU applications with extensions such as webhook and SDKs enable us in achieving required functionality. In future work, we intend to extend our chatbots for further custom and tailored functionality with deep neural network-based language models such as LSTM and Transformers.

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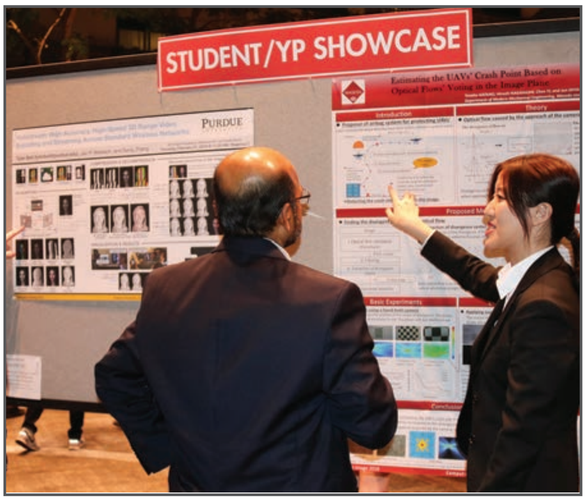

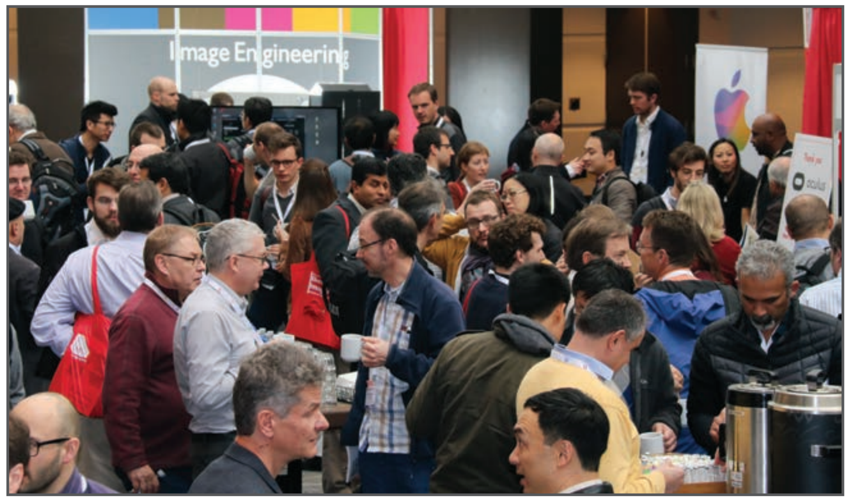

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