Personalized Employee Training Based on Learning Styles Using Unsupervised Machine Learning

Sandeepkumar Racherla
https://orcid.org/0000-0002-8155-5643

Abstract

Advancement in technology, artificial intelligence, and machine learning have resulted in an explosion in the creation of tech-enabled training solutions over the past decade, contributing to the popularity of personalized learning. This research advocates for a transition away from archaic, rote learning paradigms and toward individualized employee learning experiences in which instructional styles and training tactics are tailored to the requirements of each individual employee rather than standard lesson preparation that exist today. This technique can also foster enjoyable and engaging training environments that benefit both employees and the organizations. We applied unsupervised machine learning algorithm, namely, K-means, and Hierarchical clustering algorithms to classify 1000 employees into different clusters based on the Felder-Silverman Learning Styles Model (FSLSM). As expected, no one of the employees could be precisely classified into a single category, and they demonstrated a variety of learning methods and tactics. The experiments showed 3 significant clusters across the different pairs of Processing, Input, Understanding, and Perception dimensions of the FSLSM. The findings suggest that employees can be grouped into at least 3 clusters to create personalized training materials and approaches for each group. We also discussed suitable instruction techniques, contents, and paths for each cluster. The proposed model and the findings would work in both digital and offline settings.

Keywords: *Employee, FSLSM, Learning styles, Machine learning, Personalized training*

Introduction

The incredible impacts of the swift integration of technology disruption and digitalization with the arrival of the 4th Industrial Revolution have led many firms trying to keep up with quick changes in the workplace (Schwab, 2018). Investing proactively in employee training and growth is crucial for both the success of the organization and the workforce that pushes it, given this digital transformation and the widening digital skills gap. Filling the company's skill shortages via developing skills and retraining of employees became more important in surviving the shift.

Employees are trained to learn new skills that will help them perform better. Training sessions are often administered on a brief arrangement with a set completion date. Training is to provide workers with the opportunity to learn new skills and knowledge. Usually, training programs are created with the employee's work position in mind. The trainer and the employee exchange information. Training activities are often extremely sophisticated and do not need individualization for each employee. A

Cite this research:
Racherla, S. (2019) 'Personalized Employee Training Based on Learning Styles Using Unsupervised Machine Learning', *Reviews of Contemporary Business Analytics*, 2(1), pp. 1–11.

development program is one that focuses on improving existing skills (Falola, Osibanjo and Ojo, 2014). An ongoing and lengthy process tied to an employee's personal growth and progress is an employee development. The program puts a great importance on an employee's total personal development, which is not necessarily tied to technical aspects of his profession (Brown, 2001). Since training plans must be tailored to each individual worker, no two programs are identical.

Frequently, new methods, techniques, data and software are introduced to the business market via technology. Employees must adjust to the changes in order to stay up. It takes effort and time to learn new talents and generate new concepts (Puhakainen and Siponen, 2010). Furthermore, a business cannot anticipate its staff to be aware of things on their own. As a result, training staff to acquire new skills and information can only benefit an organization in the long term. To increase productivity and creativity, effective staff learning and development platforms must be provided. This raises their morale and works as a motivator, encouraging them to perform far more than before and participate to the company 's growth.

Employees' professional advancement is weakened by a lack of suitable training and development opportunities. Their abilities deteriorate and they feel bored in their work. Attitude refers to an employee's sentiments, viewpoint, response, and opinions toward others. It has a significant effect on an employee's morale, inspiration, commitment, dedication, and satisfaction. When an organization provides a training and development, it demonstrates that it cares about its workers' progress and well-being. This encourages people to have a good attitude about the company. More importantly, it provides them with a feeling of security and devotion to the business. When conducting performance reviews with employees, organizations normally identify areas for skill growth or knowledge enhancement (Elnaga and Imran, 2013). Offering training programs accessible enables staff to develop meaningful measures to enhance their performance at work by attending courses, therefore meeting the criteria of a performance review.

Personalized employee training

Personalized learning, often known as customization, refers to a wide range of educational initiatives, learning experiences, instruction strategies, and academic-support measures designed to accommodate individual employee' unique learning requirements, interests, goals, or cultural differences.

Today's workforce is more dispersed than ever before, with members working from home, in temporary locations, while traveling, or in a combination of these. Work schedules are always shifting, and recruiting is on the increase. As a result, businesses must implement a tailored training plan to meet staff where they are in order to guarantee relevant training is delivered in a relevant and productive manner (Maity, 2019).

Personalized training focuses on individual learners' requirements, aptitudes, and preferences. Although it is hardly a new idea, it has grown in popularity in many nations over the past decade or so. Every employee can gain when it comes to personalized learning. Employees gain from career progression chances that are directly related to their objectives, while employers save time by not having to search outside the business for talents that can be developed within. Organizations may make proper use of the skill and experience that exists inside them by engaging with people to build up personalized learning routes.

Personalization learning alleviates information overload since employees do not need to acquire a large amount of material. They just learn what is advantageous to them at the moment. Instead of spending time screening out irrelevant learning resources, employees can concentrate on acquiring useful knowledge (Dorobăt and Năstase, 2010). Corporations arrange training for a big number of workers. While group engagement may be appealing to workers, it may be inefficient for the company. While some of employees may need training, others may not. As a result, customized training allows the company to involve relevant staff in appropriate learning sessions. This enables the process to become more efficient for both personnel and the corporation.

When staff are not inspired by the training approach an organization is utilizing, they will not be engaged, which results in underperformance. As a result, the organization should personalize training to the requirements, preferences, and learning styles of its staff. Personalized training can also boost their productivity. Employees learn just what they require to perform a job when extraneous knowledge eliminated via individualized training (Peretz *et al.*, 2011). As a result, they will devote considerable time on productive work and less time on useless training.

Organizations have a diversified workforce, which implies that each employee has a unique working style and perspective. While some people love gamification, others prefer the traditional physical rules. Furthermore, some workers may enjoy interactive videos and animations, but others may prefer to read and comprehend. Organizations must thus offer customized learning procedures based on the learning styles and interests of their workers. They will be engaging with increased outcomes and certain results when they are in their area of expertise.

Scheduled training as component of a business culture is not appealing to workers. It has probably be seen how uninterested and distracted some workers are during routine training sessions. In such a case, tailored training is rather intriguing (Amoroso and Reinig, 2004). They are not really the regularly planned training sessions that are available to workers, but rather a more customized session designed specifically to match their requirements. The added advantage is that individualized learning may begin even when organizations believe workers need further knowledge (Amoroso and Reinig, 2004; Kong and Jogaratnam, 2007). Organizations may deliver such instruction to their employees on time in order to get more effective outcomes.

Methods

FSLMS

We applied Felder-Silverman Learning Styles Model (FSLSM) to group employees to different clusters based on 8 variables under 4 dimensions (Graf *et al.*, 2007; Ciloglugil, 2016; Nafea, Siewe and He, 2019). The FSLMS classifies learners in 4 dimensions, where each dimension represents 2 variables.

Table 1. FSLSM dimensions and learning styles

Dimensions	Styles	descriptions
Processing	Active/Reflective	**Active** learners learn via experimentation and love working together in groups (Joseph and Abraham, 2017). Learning via contemplation and preferring to work alone characterize the **reflective** learner.
Perception	Sensing/Intuitive	**Sensing** learners are tangible thinkers who are practical and focused on facts and processes. **Intuitive** learners are conceptual thinkers who are inventive and theory-oriented (Graf *et al.*, 2007).
Input	Visual/Verbal	**Visual** learners enjoy visualization tools of provided content. Examples include images and flow charts. **Verbal** learners tend to favor explanations in both written and spoken form (Graf, 2007).
Understanding	Sequential/Global	**Sequential** learners have a linear thought process and learn in little incremental stages. **Global** learners are comprehensive thinkers who learn in big moves (Graf, Viola and Leo, 2006).

K-means

Clustering is a well-known task in both machine learning and mathematical modelling. The k-means approach is a popular clustering method that aims to reduce the mean squared distance among points inside the same cluster (Maimon and Rokach, 2005). Lloyd's technique, often known as k-means, starts with k arbitrarily defined centers that are normally picked evenly *and arbitrarily* from the data sets. The closest center is then allocated to each point, and every center is recalculated as the mass centers of all points allocated to it. These two phases (assignment and center computation) are continued until the process reaches a state of stability.

The Clustering method use the K-Means approach to group data sets based on their degree of resemblance to the supplied metrics (Wu, 2012). Clustering may aid in the discovery of unique groups within data that need specific attention. The K-means clustering approach separates a collection of data known as n into k groups, with each observation allocated to the cluster with the average value that is nearest to its own.

This is an iterative technique where each data item is allocated to a cluster, and data points are progressively clustered based on features that they share. The aim is to discover a technique to minimize the overall distance that isolates the sets of data from the the cluster's center to its shortest feasible value in order to identify which section of the group each single data point should be a member of (Guptal, Rao and Bhatnagar, 1999; Kutbay, 2018).

To accomplish its aim of decreasing the sum of point-to-centroid distances determined over all k clusters, K-means adopts a two-phase iterative technique. During the first phase, each cycle is composed of redistributing points to their nearest cluster centroid at the same time, followed by cluster centroids being adjusted. The second step involves reallocating points each one at a moment if this results in a lower overall total of distances. After each reassignment, the centroids are recomputed. The purpose of the K-means method is to choose centroids with the lowest number of inertia possible:

$$\sum_{i=0}^{n} \min_{\mu_j \in C}(\| x_i - \mu_j \|^2)$$

Inertia is considered to be a crucial parameter for determining how cohesive and integrated clusters are.

Hierarchical Clustering

The initial stage in hierarchical clustering is to regard each data to be its own separate cluster. Next, it cycles through the following 2 steps: (1) select the two clusters that are most closely connected with one another, then (2) join the clusters which are the most related (Kassambara, 2017; Malik and Tuckfield, 2019). This iterative procedure will be repeated until all the clusters have already been consolidated into one.

When the approach is used correctly, the distances are kept in a structure known as the proximity/closeness matrix, designated by the letter M. This matrix shows the distance between the i-th and j-th clusters at the place given by the symbols "i,j." $M_{ij} = M(X_i, X_j)$ (Nitya Sai, Sai Shreya and Anjan Subudhi, 2017; Lim *et al.*, 2019).

As a consequence, in the first repeat, the proximity matrix is a N by N matrix containing just the pairs of distances calculated between our sample points using the chosen metric. $M_{ij} = m(x_i, x_j)$ (Müller and Hamm, 2014; Lin *et al.*, 2017). When small clusters are combined into larger ones, the

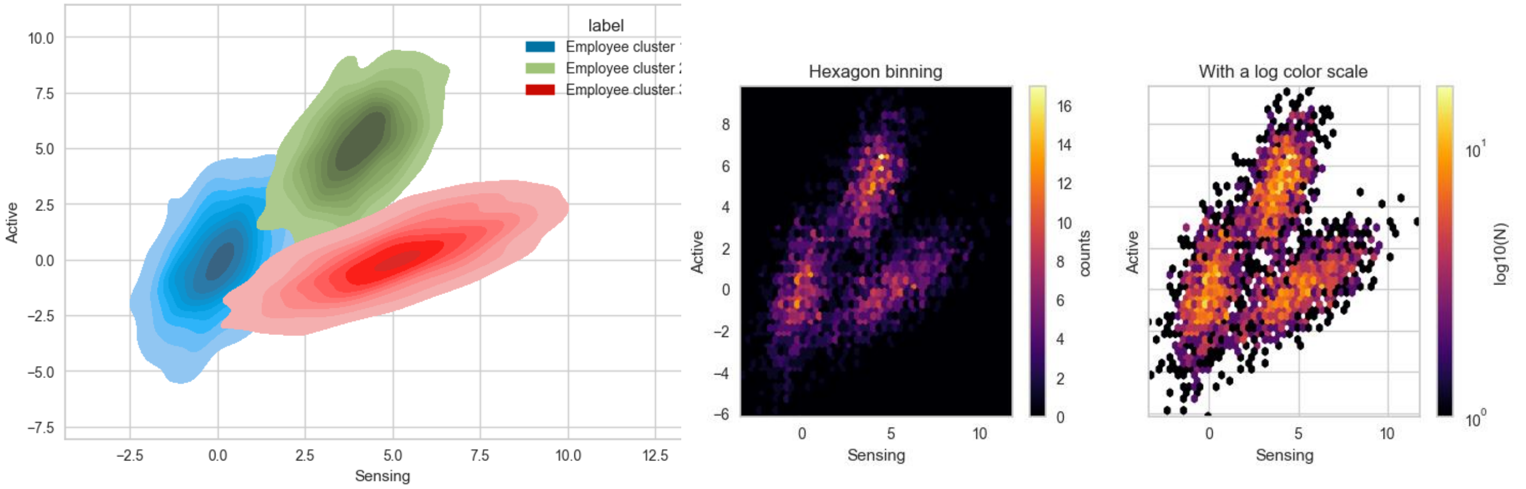
distance matrix is updated, which entails removing rows and columns. The procedure will terminate when there is just one cluster remaining that includes all of the points.
The clustering findings are often shown in the shape of a dendrogram, that shows the manner in which the different groups were joined. Because picking on a degree on the dendrogram ultimately determines data splitting and grouping. This selection could be made, for example, by passing an input to the algorithm that defines the desired clusters.

Results and discussion

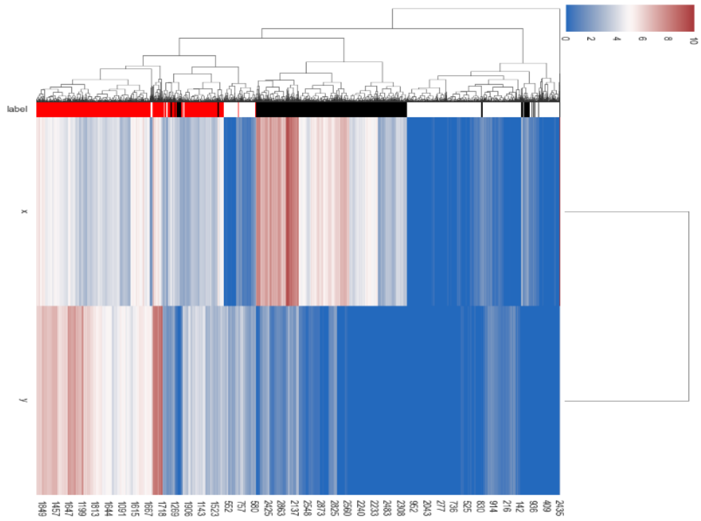
Figure 1, 2, and 3 shows the clusters of employees on different dimensions of learning styles. It can be seen that there are 3 different employee clusters in all cases under K-means clustering algorithms. The first cluster in figure 1 are the employees who are less active learner (more reflective) and less sensing learners (more intuitive). The second cluster is composed of the employees who are more active learners (less reflective) but less sensing learners. The employees who are more sensing but less active learners are in the third cluster. The figure 2, and the figure 3 displays almost similar results. Thus, it is possible to split employees into 3 groups for more personalized training experiences. The dendrograms also found 3 clusters under Hierarchical Cluster Analysis. We reported only the pairs where active/reflective is on y-axis. The reports of other 3 pairs were omitted for brevity; as the results are almost similar.

For active learners, group learning or workplace collaborative training are suggested. According to the studies (Fischer, 2000; Leong, Narunan and Sim, 2010; Lee and Bonk, 2014), workplace collaborative training promotes professional growth by allowing for collaboration, debate, and problem-solving. Instead of studying alone, colleagues are learning from one another. Active learner employees find group learning more interesting and retain more of what they learn. Group learning directly boosts employee performance of the active learner employees and their learning capacity. The company encourages its workers to provide and receive honest evaluations on one another's efforts. They also have the opportunity to be part of a cohesive community that supports them. Group training is a wonderful method for motivating individuals to learn and advance in their jobs. It allows workers to discuss different points of view and learn new things.

Figure 1. Employee clusters based on Active/Reflective and Sensing/Intuitive learning styles



Cite this research:
Racherla, S. (2019) 'Personalized Employee Training Based on Learning Styles Using Unsupervised Machine Learning', *Reviews of Contemporary Business Analytics*, 2(1), pp. 1–11.



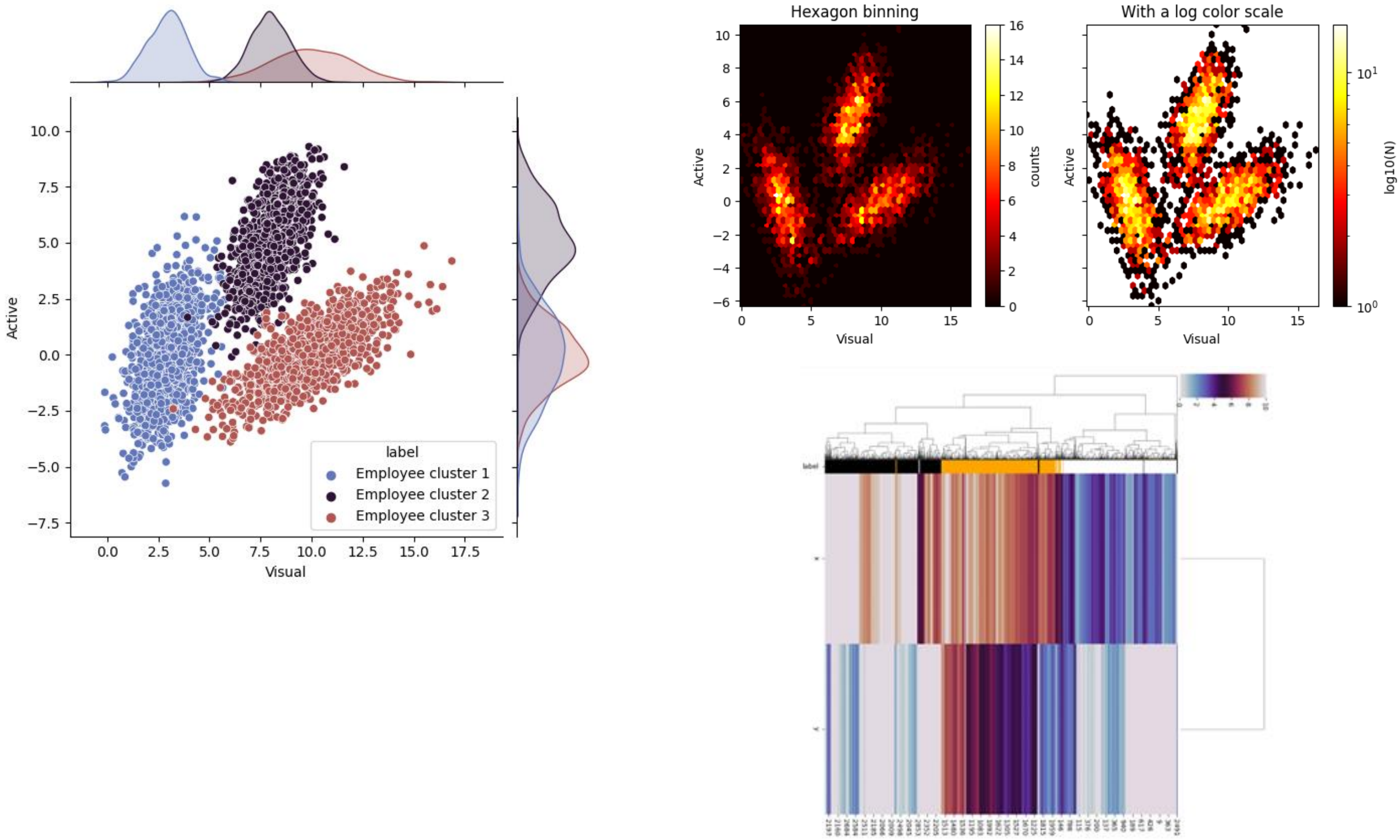
Some employees, however, prefer to learn alone as seen in figure 1, 2, and 3. Reflective learners like to study alone and are therefore more likely to benefit from self-study possibilities. It enables people to determine their learning requirements, analyze the success of their learning tactics, and regain motivation and self-assurance by reflecting on prior self-learning activities. Self-directed learning is most likely to occur when workers feel responsible for expanding their knowledge.

Self-directed learning moves accountability from the company to the individual. The employee takes charge, picking their own training curriculum based on their own learning requirements and interests. Employees are more involved in their learning when they have a personal interest in it. They learn quicker because they choose things that interest them. In addition, there is a better degree of involvement overall, which contributes to improved staff morale and productivity.

Employees who are sensing learners recall knowledge best when it is connected to the actual world, therefore placing the knowledge into real life scenarios would benefit a sensor learner. Sensors recall and comprehend information better when they understand how it relates to the actual world. They may struggle when they are in a session where the majority of the content is theoretical. They need concrete illustrations of how ideas and processes work in practice. If the trainer or the organization are not providing them enough information, they should look for them in their manuals or other sources, or brainstorm with coworkers.

Employees who are intuitive learners tend to focus on possibilities. They despise repetitive tasks since they like learning new things. They can rapidly learn new information and will typically seek for fresh approaches to achieve answers rather than employing the same one. Many courses can be designed for intuitive-learning employees. However, if the trainers put intuitive employee in a program that focuses heavily on remembering and memorization, they will most likely get uninterested. These employees should be offered interpretations or hypotheses that connect the data, or they must be given the chance to attempt to identify the connections for themselves. Because they are bored with nuances and dislike repetition, those employees may make thoughtless errors in applying the learned things.

Figure 2. Employee clusters based on Active/Reflective and Sensing/verbal learning styles

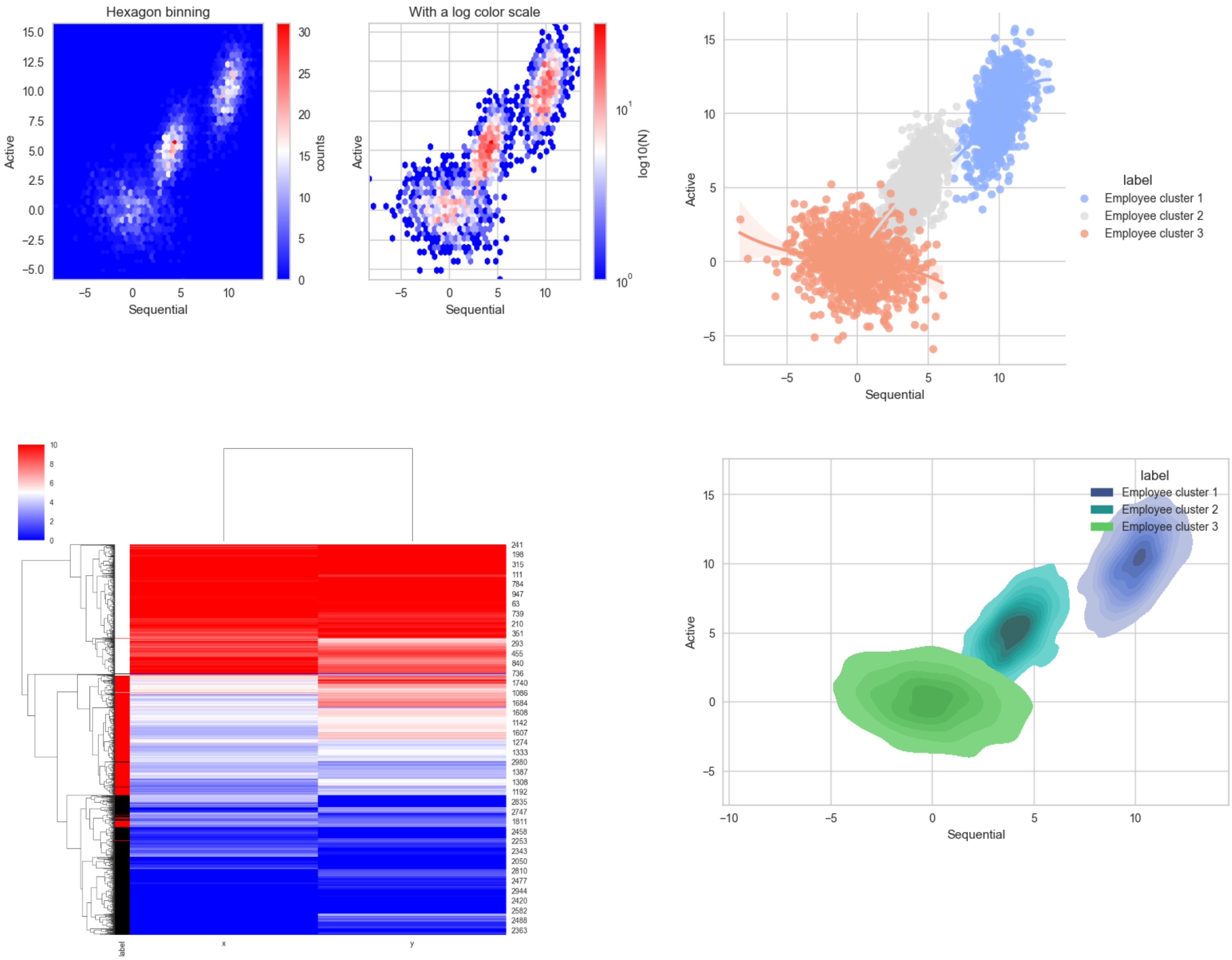


Images, charts, process flow, plot lines, videos, and multimedia presentations are the most memorable for employees who are visual learners. Verbal learners benefit more from textual and oral instructions. When knowledge is given both visually and vocally, everyone learns more. Since most individuals are visual learners, the absence of visual presentation severely limits most learning. It is necessary to make heavy use of diagrams, drawings, schematics, pictures, flow charts, and other visual representations of normally primarily spoken content.

Employees who are verbal leaners should be allowed and encouraged to create their own descriptions or summaries of training contents. Working in groups may also be beneficial: kids acquire comprehension of topic by hearing peers describe it, and they understand even better when they express it themselves. Working in groups may also be beneficial: employees may acquire comprehension of topic by hearing co-workers describe it, and they understand even better when they express it themselves.

Cite this research:
Racherla, S. (2019) ‘Personalized Employee Training Based on Learning Styles Using Unsupervised Machine Learning’, *Reviews of Contemporary Business Analytics*, 2(1), pp. 1–11.

Figure 3. Employee clusters based on Active/Reflective and Sequential/Global learning styles



Employees who are sequential learners often develop comprehension in linear phases, with each step logically preceding the previous one. Sequential learners solve issues in logical sequential sequences.

The majority of training materials are delivered in a sequential order. If the employees are sequential and the training contents move from subject to topic or miss out stages, they may struggle to follow and recall. They will be required to persuade the trainers to complete the gaps, or they will have to seek references to do so. When studying, individuals should spend some time creating a logical overview of the course content for themselves. They may also attempt to improve their global thinking abilities by linking each new subject they learn to something they already know. The more they are able to accomplish this, the more probable it is that they will have a thorough comprehension of the material.

Global learners have a tendency to learn in enormous leaps, absorbing data almost arbitrarily without noticing connections and then "getting it." Once they get the broad picture, global learners could be able to solve complicated issues quickly or integrate things together in creative ways, but they may struggle to articulate how they accomplished it.

If the employee are global learners, it might be beneficial for them to understand the overall picture of a topic before they can understand the intricacies. If the training contents go right into new subjects without explaining how they connect to what the employees currently know, they may struggle. Fortunately, there are actions people may take to obtain a better sense of the broader picture faster. They should scan over the full materials before beginning to read the first portion. This may take some time at first, but it may help them avoid having to go over particular areas later. Rather than spending a small amount of time on each topic every training session, they may find it more beneficial to engage themselves in certain subjects for extended periods of time.

Conclusion

Outdated, and non-personalized learning methods may have a negative impact on how prospective and current workers view the organization. A customized learning process is the modification and adaption of educational processes and procedures such that the process of learning is ideally adapted to every single employee or group of employees, with their own distinct learning style, culture, requirements, and prior experience.

Leading firms have spent considerably in employee training in recent years because the advantages to employers are vast and diversified. Employee training has lately emerged as a critical corporate strategy for not only retaining workers but also developing a trained future workforce. Irrespective of whether an organization has established, functional training programs, staff growth can never be successful until the work environment allows for - and encourages - ongoing learning. Organizations must foster a culture of continuous growth capable of recognizing broad industry change and providing suitable training to tackle the obstacles that such changes may bring.

The advent of digitalization has made it imperative for businesses to rapidly increase the skill sets of their employees, but the methods that were effective in the past will no longer suffice. Learning and development programs are increasingly seen as strategic partners involved in developing vital skills in the workplace and enhancing the entire employee experience. Personalized learning is becoming more popular, and it is an excellent approach to ensure that the employees are learning efficiently, creatively, and in a manner that will have a good and long-term impact.

References

Amoroso and Reinig (2004) “Personalization Management Systems: Minitrack Introduction,” in *37th Annual Hawaii International Conference on System Sciences, 2004. Proceedings of the*. computer.org, p. 70201.

Brown, K. G. (2001) “Using computers to deliver training: Which employees learn and why?,” *Personnel psychology*. Wiley, 54(2), pp. 271–296.

Ciloglugil, B. (2016) “Adaptivity based on Felder-Silverman learning styles model in E-learning systems,” *4th International Symposium on Innovative Technologies in Engineering and Science (ISITES2016) 3-5 Nov 2016 Alanya/Antalya - Turkey*. isites.info. Available at: https://www.isites.info/PastConferences/ISITES2016/ISITES2016/Allpapers/C1-ISITES2016ID219.htm.

Dorobăt, I. and Năstase, F. (2010) *Personalized training in Romanian SME’s ERP implementation projects*. revistaie.ase.ro. Available at: http://www.revistaie.ase.ro/content/55/2001%20-%20Iulia%20Dorobat,%20Floarea%20Nastase.pdf.

Elnaga, A. and Imran, A. (2013) “The effect of training on employee performance,” *European journal of Business and Management*. academia.edu, 5(4), pp. 137–147.

Falola, H. O., Osibanjo, A. O. and Ojo, S. I. (2014) “EFFECTIVENESS OF TRAINING AND DEVELOPMENT ON EMPLOYEES’PERFORMANCE AND ORGANISATION COMPETITIVENESS IN THE NIGERIAN BANKING INDUSTRY,” *Bulletin of the Transilvania University of Brasov. Economic Sciences. Series V*. Transilvania University of Brasov, 7(1), p. 161.

Fischer, G. (2000) “Lifelong learning—more than training,” *Journal of Interactive Learning Research*. learntechlib.org. Available at: https://www.learntechlib.org/p/8380/.

Graf, S. (2007) *Adaptivity in learning management systems focussing on learning styles*. repositum.tuwien.at. Available at: https://repositum.tuwien.at/handle/20.500.12708/10843.

Graf, S. *et al.* (2007) “In-depth analysis of the Felder-Silverman learning style dimensions,” *Journal of Research on Technology in Education*. Taylor & Francis, 40(1), pp. 79–93.

Graf, S., Viola, S. R. and Leo, T. (2006) *Representative characteristics of Felder-Silverman learning styles: An empirical model*. ieg.ifs.tuwien.ac.at. Available at: http://ieg.ifs.tuwien.ac.at/people/graf/publications/graf_viola_kinshuk_leo_CELDA06.pdf.

Guptal, S. K., Rao, K. S. and Bhatnagar, V. (1999) “K-means Clustering Algorithm for Categorical,” in *Data Warehousing and Knowledge Discovery: First International Conference, DaWaK’99 Florence, Italy, August 30-September 1, 1999 Proceedings*. Springer Science & Business Media, p. 203.

Joseph, L. and Abraham, S. (2017) “Instructional design for learning path identification in an e-learning environment using felder-silverman learning styles model,” in *2017 International Conference on Networks & Advances in Computational Technologies (NetACT)*. ieeexplore.ieee.org, pp. 215–220.

Kassambara, A. (2017) *Practical guide to cluster analysis in R: Unsupervised machine learning*. STHDA.

Kong, M. and Jogaratnam, G. (2007) “The influence of culture on perceptions of service employee behavior,” *Managing Service Quality: An International Journal*. Emerald Group Publishing Limited, 17(3), pp. 275–297.

Kutbay, U. (2018) “Partitional clustering,” *Recent Applications in Data Clustering*. books.google.com. Available at: https://books.google.com/books?hl=en&lr=&id=jnuQDwAAQBAJ&oi=fnd&pg=PA19&dq=clustering:++k-means+hierarchical+&ots=z85DYCsBRd&sig=saT7zBXE2NEkV-X0JdIgeLaDIng.

Lee, H. and Bonk, C. J. (2014) “Collaborative Learning in the Workplace: Practical Issues and Concerns,” *International Journal of Advanced Corporate Learning*. academia.edu, 7(2). Available at: https://www.academia.edu/download/37683089/iJAC_vol7_no2_2014--Lee_and_Bonk_Corporate_wikis.pdf#page=10.

Leong, P. C., Narunan, R. and Sim, S. (2010) “Background paper for Malaysia: Skills development in the workplace in Malaysia,” in *ILO/skills-ap/Japan regional technical workshop and study programme on skills training in the workplace overseas vocational training association, Chiba, Japan*. ams-forschungsnetzwerk.at. Available at: https://ams-forschungsnetzwerk.at/downloadpub/Skills_development_in_the_workplace_in_malaysia_2010.pdf.

Lim, K. C. *et al.* (2019) “A Comparative Usability Study Using Hierarchical Agglomerative and K-Means Clustering on Mobile Augmented Reality Interaction Data,” in *Advancing Technology*

Industrialization Through Intelligent Software Methodologies, Tools and Techniques. IOS Press, pp. 258–271.

Lin, W.-C. *et al.* (2017) “Clustering-based undersampling in class-imbalanced data,” *Information sciences*. Elsevier, 409–410, pp. 17–26.

Maimon and Rokach (2005) “Clustering methods,” *Data mining and knowledge discovery*. books.google.com. Available at: https://books.google.com/books?hl=en&lr=&id=jizrAIWUJ6UC&oi=fnd&pg=PA321&dq=cluster+Hierarchical+Clustering++&ots=mSjV2w3mfF&sig=FsSivb37M_jAlmoyTKbeHlJqORA.

Maity, S. (2019) “Identifying opportunities for artificial intelligence in the evolution of training and development practices,” *International Journal of Management & Enterprise Development*. Emerald Publishing Limited, 38(8), pp. 651–663.

Malik, A. and Tuckfield, B. (2019) “Applied Unsupervised Learning with R: Uncover hidden relationships and patterns with k-means clustering, hierarchical clustering, and PCA.” books.google.com. Available at: https://books.google.com/books?hl=en&lr=&id=_jmPDwAAQBAJ&oi=fnd&pg=PR1&dq=clustering:++k-means+hierarchical+&ots=coB1sflccM&sig=2pi3KS2vh7BabT9n0JJ_mTKgcHc.

Müller, H. and Hamm, U. (2014) “Stability of market segmentation with cluster analysis – A methodological approach,” *Food quality and preference*. Elsevier BV, 34, pp. 70–78.

Nafea, S. M., Siewe, F. and He, Y. (2019) “On Recommendation of Learning Objects Using Felder-Silverman Learning Style Model,” *IEEE Access*. ieeexplore.ieee.org, 7, pp. 163034–163048.

Nitya Sai, L., Sai Shreya, M. and Anjan Subudhi, A. (2017) “Optimal k-means clustering method using silhouette coefficient.” indianjournals.com. Available at: https://www.indianjournals.com/ijor.aspx?target=ijor:ijaritac&volume=8&issue=3&article=011.

Peretz, C. *et al.* (2011) “Computer-based, personalized cognitive training versus classical computer games: a randomized double-blind prospective trial of cognitive stimulation,” *Neuroepidemiology*. karger.com, 36(2), pp. 91–99.

Puhakainen, P. and Siponen, M. (2010) “Improving Employees’ Compliance Through Information Systems Security Training: An Action Research Study,” *The Mississippi quarterly*. Management Information Systems Research Center, University of Minnesota, 34(4), pp. 757–778.

Schwab, K. (2018) “The fourth industrial revolution (Industry 4.0) a social innovation perspective,” *Tạp chí Nghiên cứu dân tộc*. Hoc Vien Dan Toc, (23). doi: 10.25073/0866-773x/97.

Wu, J. (2012) *Advances in K-means clustering: A data mining thinking*. 2012th ed. Berlin, Germany: Springer (Springer Theses). Available at: https://books.google.at/books?id=pI2_F8SqWcQC.