1. **How can technology be used to inform patients regarding the interpretation of their thyroid testing results?**
   1. Computer technologies such as machine learning can be used to interpret diagnostic test results for the patients. Using a database built under the help of thyroid related specialists, which could provide labeling to thyroid testing and the correlated potential disease, a supervised learning classifier-based algorithm could be built. Such algorithm could help to screen patients with poor thyroid test results. Various studies have used machine learning tools to help patients make informed decisions. For example, Wu et. al. implemented a neuron network supervised learning algorithm, and trained the said algorithm recognizing and classifying histopathological proven thyroid nodules. Compared with diagnosis made by the experienced radiologist (88.66%), the said supervised learning algorithm have higher prediction accuracy (92.31%) (Wu, Deng, Zhang, Liu, & Chen, 2016). The implementation of such algorithm could potentially benefit both the healthcare provider and the patient by decreasing the manpower and finical cost.
   2. Beyond diagnosis algorithms, computational technology can also help patients to interpret their thyroid testing results through telemedicine interviews. After all algorithms cannot replace suggestions from actual doctors and nurses. Telemedicine solutions allow patients to communicate with health care providers via internet devices, such as smartphones. If the patient is not capable due to reasons such as long travel distance, the patient is incapable to travel, or during infectious disease outbreaks, telemedicine can offer patients the interpretation on their thyroid testing results, or many other kinds of testing results, from healthcare providers (Ayyagari et al., 2003; Dullet et al., 2017; Raad, 2010).
2. **How can technology be used to help doctors navigate the highly personalized future of test interpretation?**
   1. To make the future of test interpretation *personalized*, the test need to be interpreted according to the health condition of each, well, *person*. The information of health condition on each individual could be obtained via the application of big data. Various research works have discussed the possibility of applying big data in analysis and treatment of various diseases. For example, M. Chen et. al. developed an Internet of Things (IOT) based algorithm, which could track the patient’s blood sugar, blood pressure, heart rate, and other information in time via wearable device, and provide personalized diagnosis and treatment suggestions using big data (M. Chen et al., 2018).
   2. Beyond regular health care data such as blood pressure and blood sugar, more advanced details down to the omics (omics is the collective representation of genomics, proteomics, and metabolomics) level can also be measured for each individual patient, thanks to the rapid development of high‐throughput technologies. Obviously, patient’s omics data will be large in size. Big data can provide solution to perform interpretation on analyzing such personalized information, and make diagnosis and treatment suggestions. R. Chen et. al. demonstrated that it is possible to generate personal omics profile for individuals. Such information could not only reveal the genetic susceptibility of an individual, but also monitors his/her real‐time physiological states (R. Chen & Snyder, 2013)
   3. To facilitate personalized interpretation of test results, a better understanding of the patient’s systems is needed. Computational models that represent the patient’s system provide the doctors and drug developers an experimental ground with their innovative ideas. For example, a thyroid model is developed to help doctors to better understand thyroid test data, by simulating the hormone pathway that arrive and leave the thyroid stimulating hormone (Degon, Chipkin, Hollot, Zoeller, & Chait, 2008).
3. **How could ML be used to help correlate patient symptoms with test results?** 
   1. The reason why machine learning algorithm is a powerful tool to correlate patient symptoms with test result is that the ML provides high predict accuracy. However, ‘there is no free lunch (Xu, Caramanis, Mannor, & intelligence, 2011)’: the improvement of machine learning accuracy is usually associated with sacrificing the model’s interpretability. ‘Black box’ algorithms such as SVM and neuron networks are powerful in predicting, but is hard for interpret on why the algorithms will make certain decision, which is what doctors really care. Thus, more simple-structured ML algorithms (such as decision tree and naïve Bayes) are more suitable for disease-related classification, because these models enable clinicians to correlate test results with disease symptoms (Kim, Cho, & Oh, 2017).
   2. To correlate patient symptoms with test results, the ML algorithms should be coupled with big data. Big data can generate large amount of data on a personalized scale, y performing advanced biomedical measurements such as omics studies, as we have discussed above on the R. Chen example (R. Chen & Snyder, 2013), which uses big data to compare symptoms and test results.

**References**

Ayyagari, A., Bhargava, A., Agarwal, R., Mishra, S., Mishra, A., Das, S., . . . Pandey, A. (2003). Use of telemedicine in evading cholera outbreak in Mahakumbh Mela, Prayag, UP, India: an encouraging experience. *Telemedicine Journal e-Health, 9*(1), 89-94.

Chen, M., Yang, J., Zhou, J., Hao, Y., Zhang, J., & Youn, C.-H. (2018). 5G-smart diabetes: Toward personalized diabetes diagnosis with healthcare big data clouds. *IEEE Communications Magazine, 56*(4), 16-23.

Chen, R., & Snyder, M. (2013). Promise of personalized omics to precision medicine. *Wiley Interdisciplinary Reviews: Systems Biology Medicine, 5*(1), 73-82.

Degon, M., Chipkin, S. R., Hollot, C., Zoeller, R. T., & Chait, Y. (2008). A computational model of the human thyroid. *Mathematical biosciences, 212*(1), 22-53.

Dullet, N. W., Geraghty, E. M., Kaufman, T., Kissee, J. L., King, J., Dharmar, M., . . . Marcin, J. P. (2017). Impact of a university-based outpatient telemedicine program on time savings, travel costs, and environmental pollutants. *Value in Health, 20*(4), 542-546.

Kim, S. J., Cho, K. J., & Oh, S. (2017). Development of machine learning models for diagnosis of glaucoma. *PLOS One, 12*(5).

Raad, M. W. (2010). A ubiquitous mobile telemedicine system for the elderly using RFID. *IJSN, 5*(2/3), 156-164.

Wu, H., Deng, Z., Zhang, B., Liu, Q., & Chen, J. (2016). Classifier model based on machine learning algorithms: application to differential diagnosis of suspicious thyroid nodules via sonography. *American Journal of Roentgenology, 207*(4), 859-864.

Xu, H., Caramanis, C., Mannor, S. J. I. t. o. p. a., & intelligence, m. (2011). Sparse algorithms are not stable: A no-free-lunch theorem. *34*(1), 187-193.