

Circular RNAs as Potential Biomarkers in Huntington's Disease Pathogenesis

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This work was supported by:



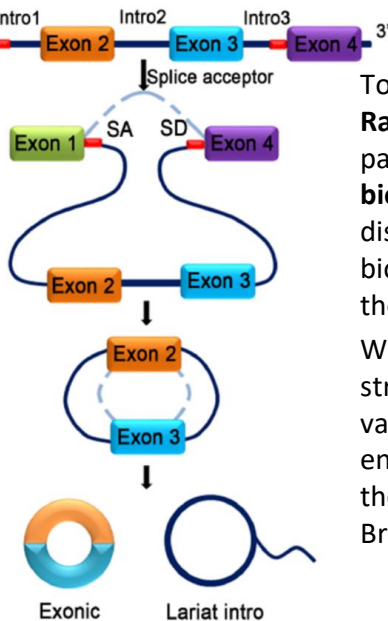
1. Introduction & Aim

Background

To date, HD patients are classified by the **Unified Huntington Disease Rating Scale (UHDRS)**, which relies on non-objectively measurable parameters, thus there is an increasing need to develop and validate **biomarkers in accessible biofluids** (such as blood) to either follow disease progression and/or to predict treatment's outcome. Such biomarkers will also be essential in assessing the effectiveness of new therapeutic treatments.

We focused on circular RNAs (circRNAs), covalently-bound, single-stranded RNA circles, obtained by backsplicing [1]. CircRNAs could be valuable biomarkers since (i) they are more stable and resistant to endonucleases than their linear counterparts; (ii) they are abundant in the Central Nervous System (CNS) [2]; (iii) they can easily cross the Blood-Brain Barrier (BBB) [3].

Sheng Xu et al., 2018



Aim

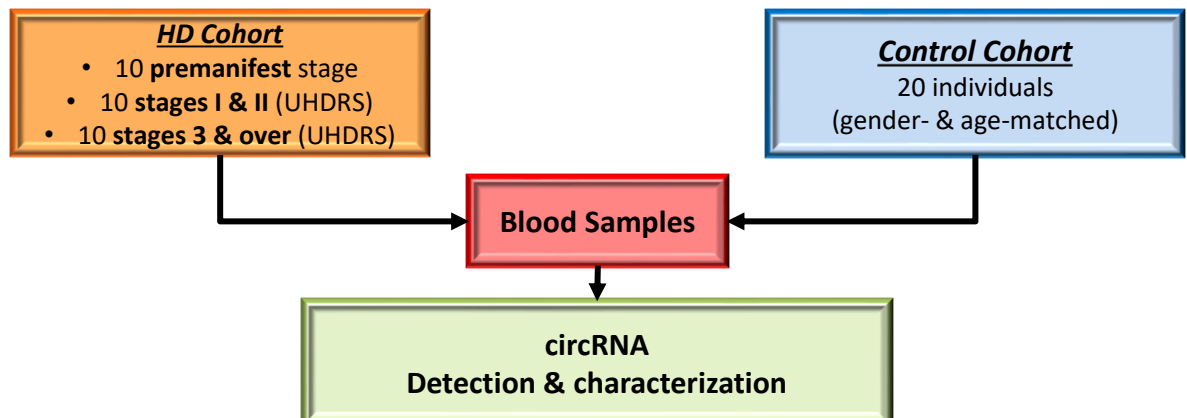
Here, for the first time in HD, we aim to focus, detect, and characterize blood-derived circRNAs. We investigate their potential as new biomarkers that can forecast the onset of motor symptoms as well as consistently follow the later stages of HD disease stage and length of the CAG repeat.

Blood Samples

50 blood samples were collected, divided in 2 cohorts: a **HD Cohort**, composed of **30 individuals** affected by Huntington at different stages of the disease; a **Control Cohort**, comprising of **20 healthy, age and sex-matched individuals**. The **Blood Samples** were provided Prof. **Ferdinando Squitieri** (Huntington and Rare Diseases Unit in Rome).

This protocol was **approved by the appointed ethical committee** and all those involved signed a form of **informed consent**.

Fig. 1



Results 1. Sequencing quality control

We first examined the number of read counts for all samples, specifically the reads mapping to unique loci in the genome, as they are indicative of the quality of the library: 2 samples of the asymptomatic stage (HD26 and HD37) had a number of reads outside of the 'Mean \pm 2SD' range, and were removed from downstream analyses (Fig. 2A). We also examined the chimeric reads, used to detect and quantify circRNAs (Fig. 2B).

Fig. 2A

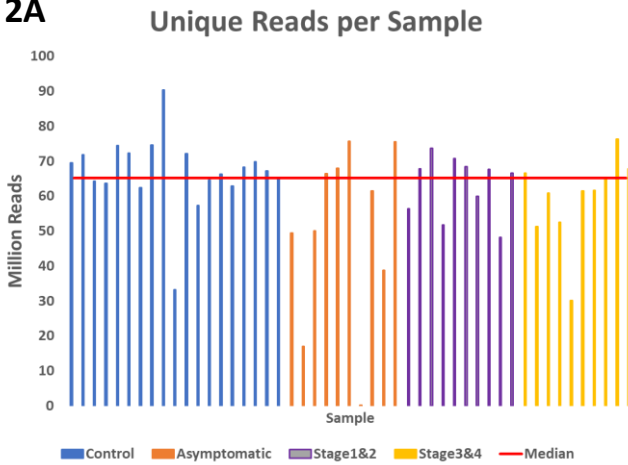
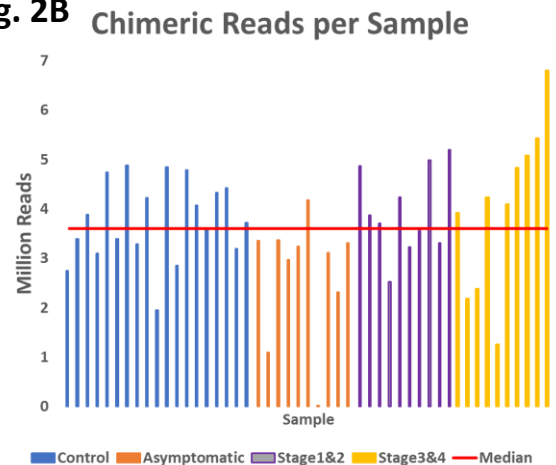


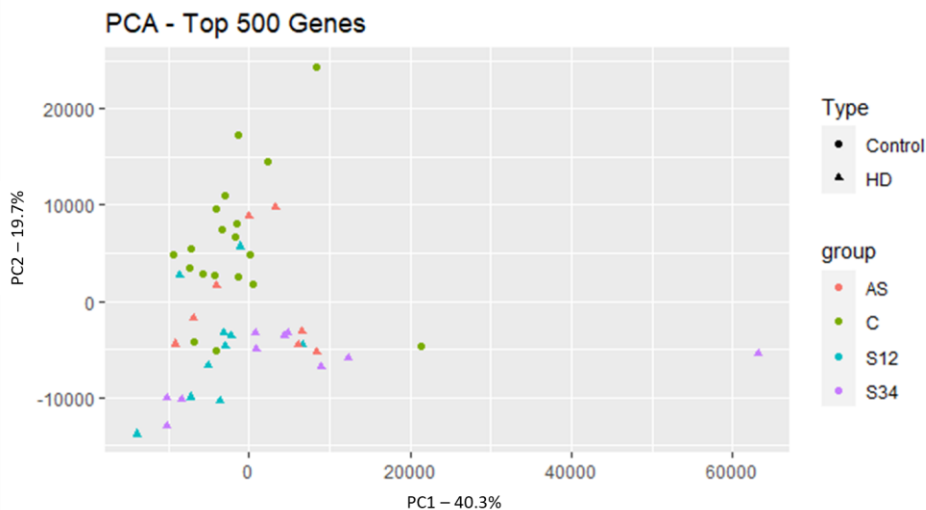
Fig. 2B



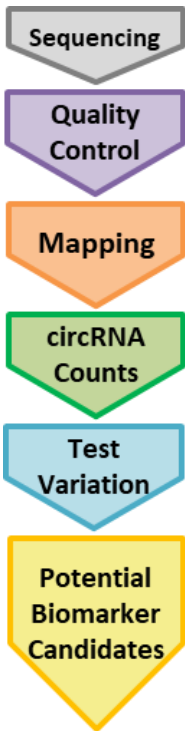
Principal Component Analysis

Using **STAR-generated gene counts**, we performed PCA analysis, using the top 500 genes with highest variance across samples (Fig. 3). A clear separation between Controls (green dots) and the HD group (orange, cyan and purple triangles).

Fig. 3

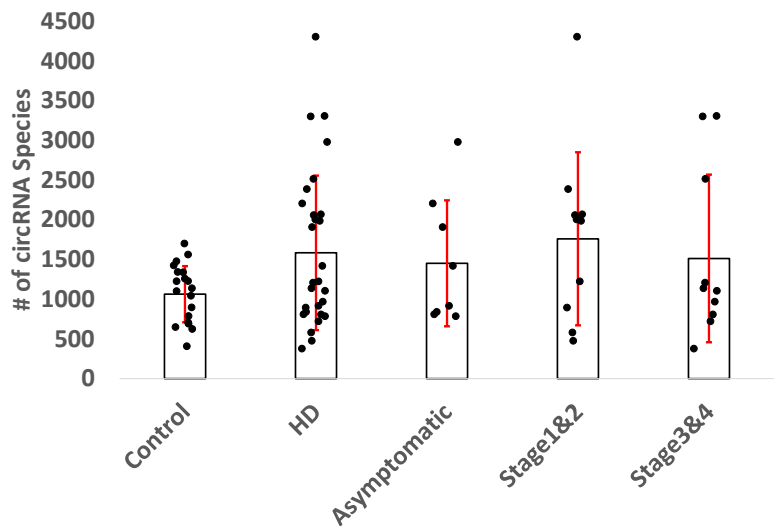


Results 2. CircRNA expression is dysregulated in HD patients



By applying the bioinformatic pipeline depicted in the diagram [4-6], we evaluated the overall number of different species of circRNA present in each of the 2 main conditions (CTRL vs HD). Only circRNAs with a number of counts per sample ≥ 3 in either group were considered (Fig. 4). **As shown in the figure, the control group has a lower average number of expressed circRNA species when compared to the patient group (whether considered as a whole – ‘HD’ bar – or stage by stage: asymptomatic, Stage 1&2, Stage 3&4).**

Fig. 4 # circRNA Species per Sample

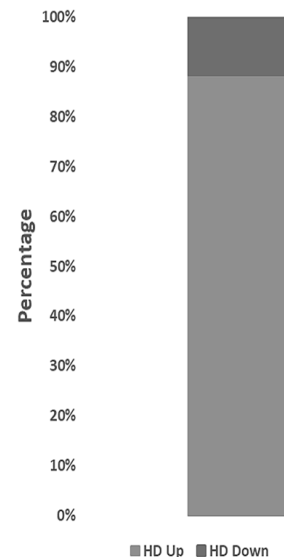


Most circRNAs are upregulated in HD patients

Among all the detected circRNA, 88.3% were up-regulated in HD, while the remaining were down-regulated (Fig. 5).

	# circRNA	%
HD Up	730	88.3
HD Down	97	11.7

Fig. 5 Disregulated circRNA in HD compared to Control



Results 3. Selection of viable circRNAs candidates

CircTest: Control vs HD group differentially expressed circRNA

With **CircTest** we were able to identify **35 circRNAs** whose expression was enriched in HD patients (as a whole) compared to controls (Fig. 6A). **GO and KEGG** pathway analysis of the obtained list, revealed that these genes are predominantly involved to **ubiquitination-related** pathways (Fig. 6B).

Fig. 6A

35 differentially expressed circRNA found

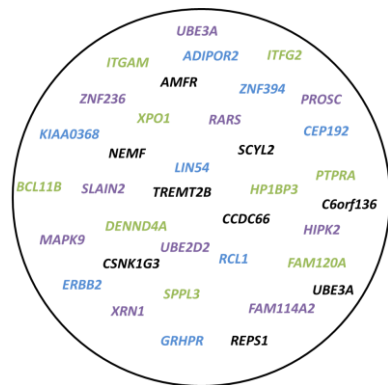


Fig. 6B

reg. of ubiquitin-mediated prot. cat. proc.

-log₁₀(P-value adj.)

prot. K48-linked ubiquitination

prot. autoubiquitination

adiponectin-activated sign. pathway

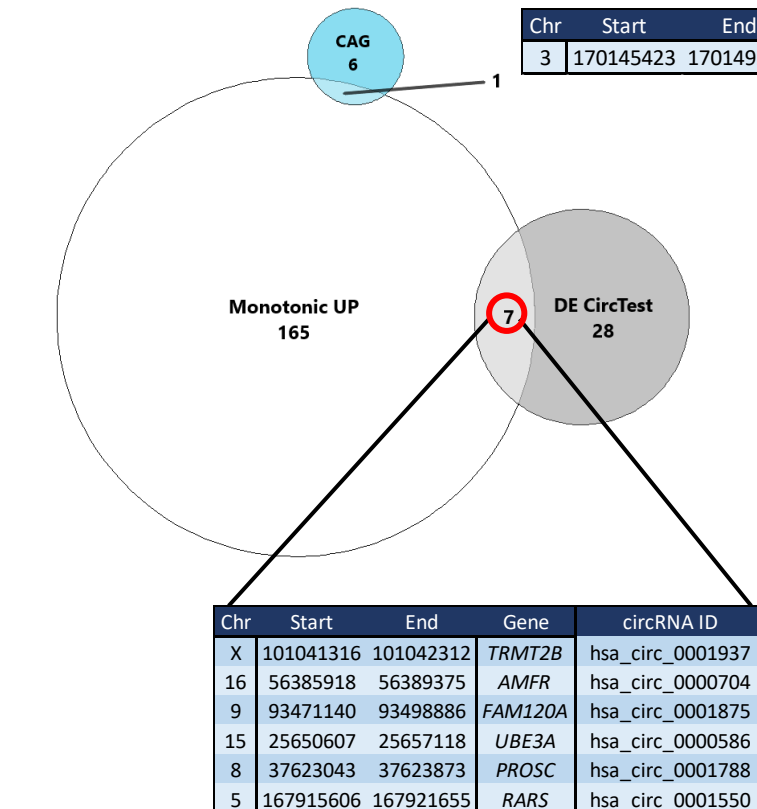
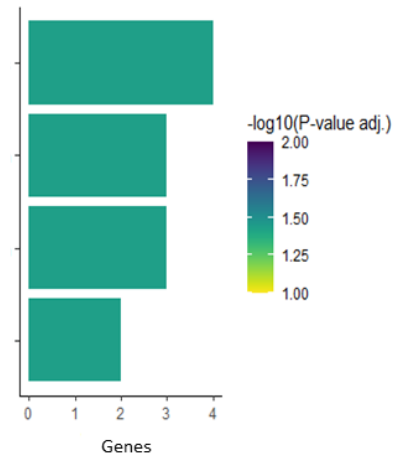


Fig. 7

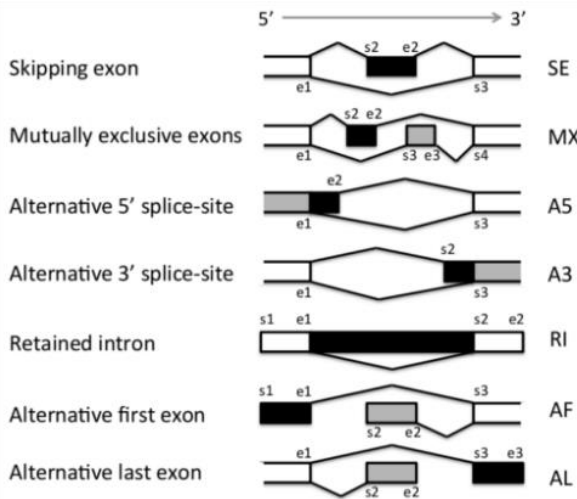
To identify a suitable list of circRNAs candidates, we intersected the results from 3 analytical approaches :

- 1) circRNAs differentially expressed in HD;
- 2) circRNAs whose expression increases with disease progression;
- 3) circRNA correlated to the CAG length.

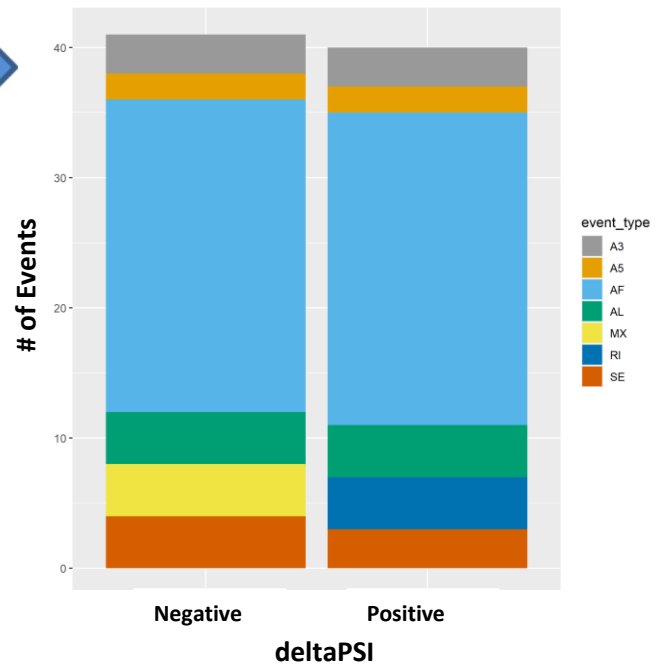
7 circRNA candidates were identified that satisfied conditions 1) and 2), while 1 satisfied conditions 2) and 3) (Fig. 7).

Results 4. Alternative Splicing Analysis in HD Blood Samples

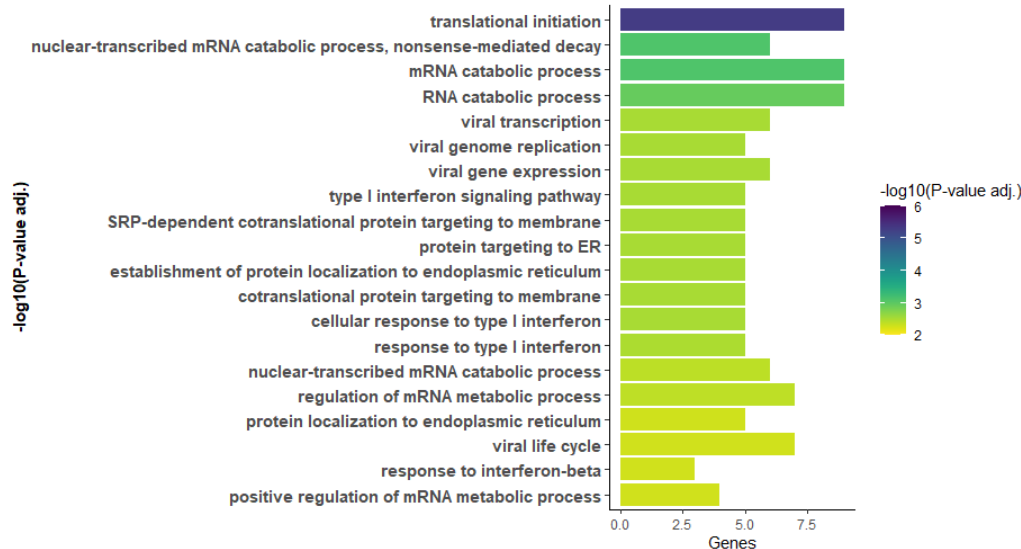
We investigated **Alternative Splicing events (AS)** that may differ between the HD and Control groups. Transcripts were first quantified with **Kallisto** [7] and then the difference in 'Percentage of Spliced-In' (dPSI) was calculated with **SUPPA2** [8,9]. **81 splicing events** reached significance (**P-value < 0.05**) with a **dPSI above 10%** in the HD group compared to the control. Even if only few events show a significant difference, it is still possible that one or more of these may be of particular relevance for the disease, thus further analyses concerning this topic are required.



(Adapted from: Alamancos G.P. et al., 2015)



GO and KEGG pathway analysis for the genes related to the identified events: here we report the 20 most significant. Most of the reported terms are related to **RNA processing, Interferon response** and **protein localization**. RNA processing is a well established process that is disrupted by *mutHTT*: alterations in the functioning of this pathways might lead to alterations in splicing and, possibly, to backsplicing.



Results 5. Gene expression in HD Blood Samples

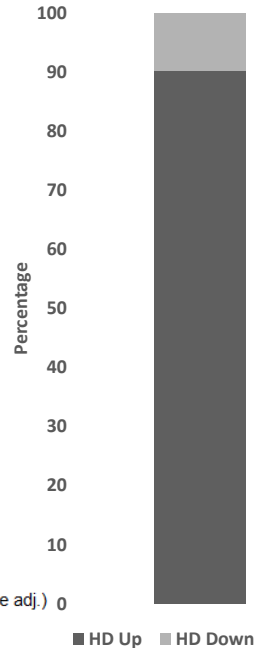
Most Differentially Expressed Transcripts are Up-regulated in HD



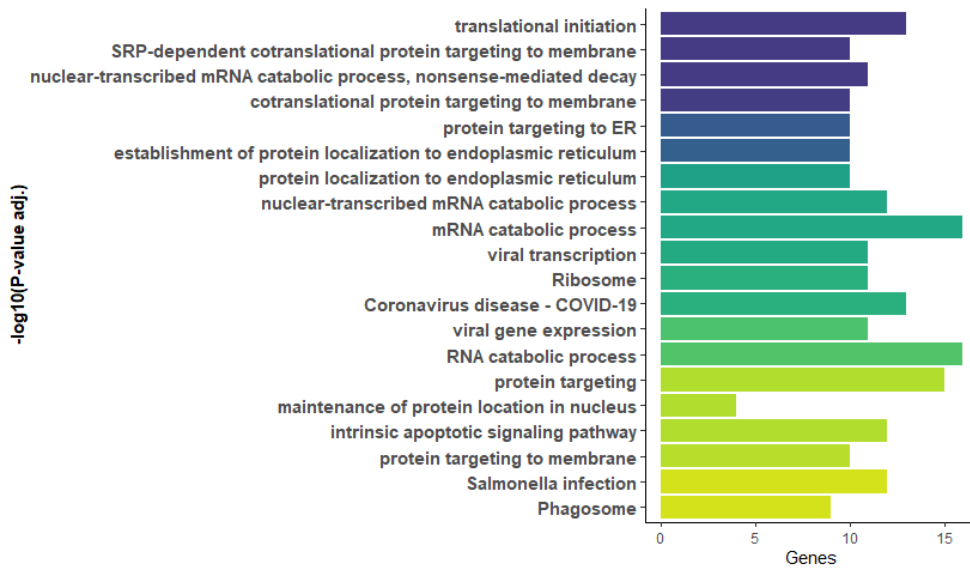
Transcript counts obtained with Kallisto [10] were used as input for DESeq2 [9]. After the removal of Globin and rRNA transcripts, 287 transcripts resulted differentially expressed (adjusted P-value < 0.05, |logFC| > 0.5), of which >90% are enriched in HD.

Some of the most prominent processes that emerged from the **GO and KEGG** pathway analysis for these genes include: 'intracellular transport', 'RNA processing'.

Differentially Expressed Transcripts

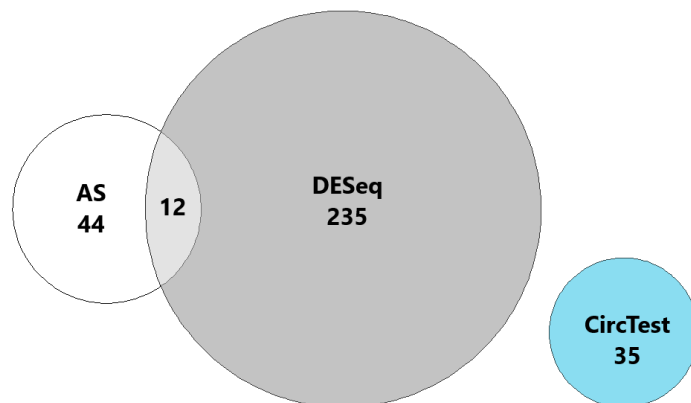


	DE	%
HD Up	259	90.2
HD Down	28	9.8



Intersection between AS events, DE transcripts and circRNA

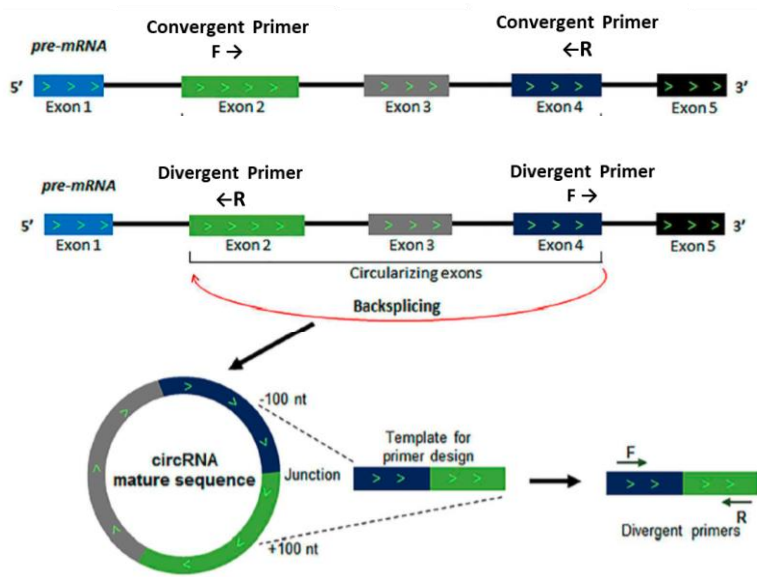
We intersected the gene lists obtained from AS, DESeq and CircTest analyses to verify whether the observed changes in AS and circRNAs expression could be linked to differential expression. As evidenced by the Venn diagrams, the overlaps are really minimal, suggesting that mutHTT is affecting the AS and backsplicing processes independently of gene expression changes.



Future Directions

Validation of the circRNA candidates identified by RNA-seq via RT-qPCR assay to detect and quantify these possible new biomarkers and

1. Segregate HD patients based on the disease stage.



Specific circRNA amplification will be achieved through the use of Divergent Primers.

(Image adapted from Panda A. C. and Gorospe M, "Detection and Analysis of Circular RNAs by RT-PCR", 2018).

- 2. Evaluate reproducibility** of our findings in a **different cohort** of patients;
- 3. Comparison** between **newly identified** biomarkers and the **pre-existing** ones, specifically **how they change in relation to mutHTT levels**;
- 4. Evaluate** if the candidate behave similarly **in the Cerebro Spinal Fluid (CSF)** as they do in **blood**.



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